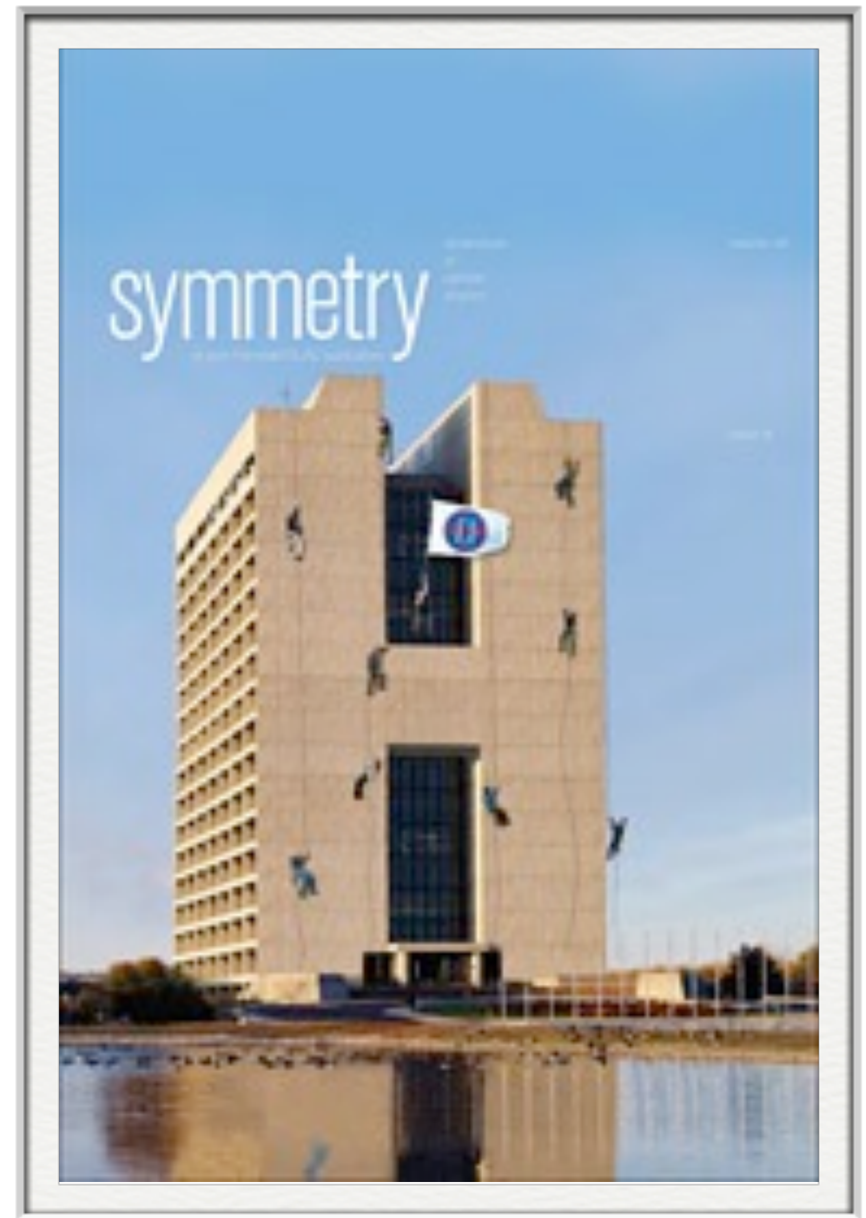
Learning to Accept Higgs Boson at CDF

Sarah Lockwitz, Yale University
January 17, 2012

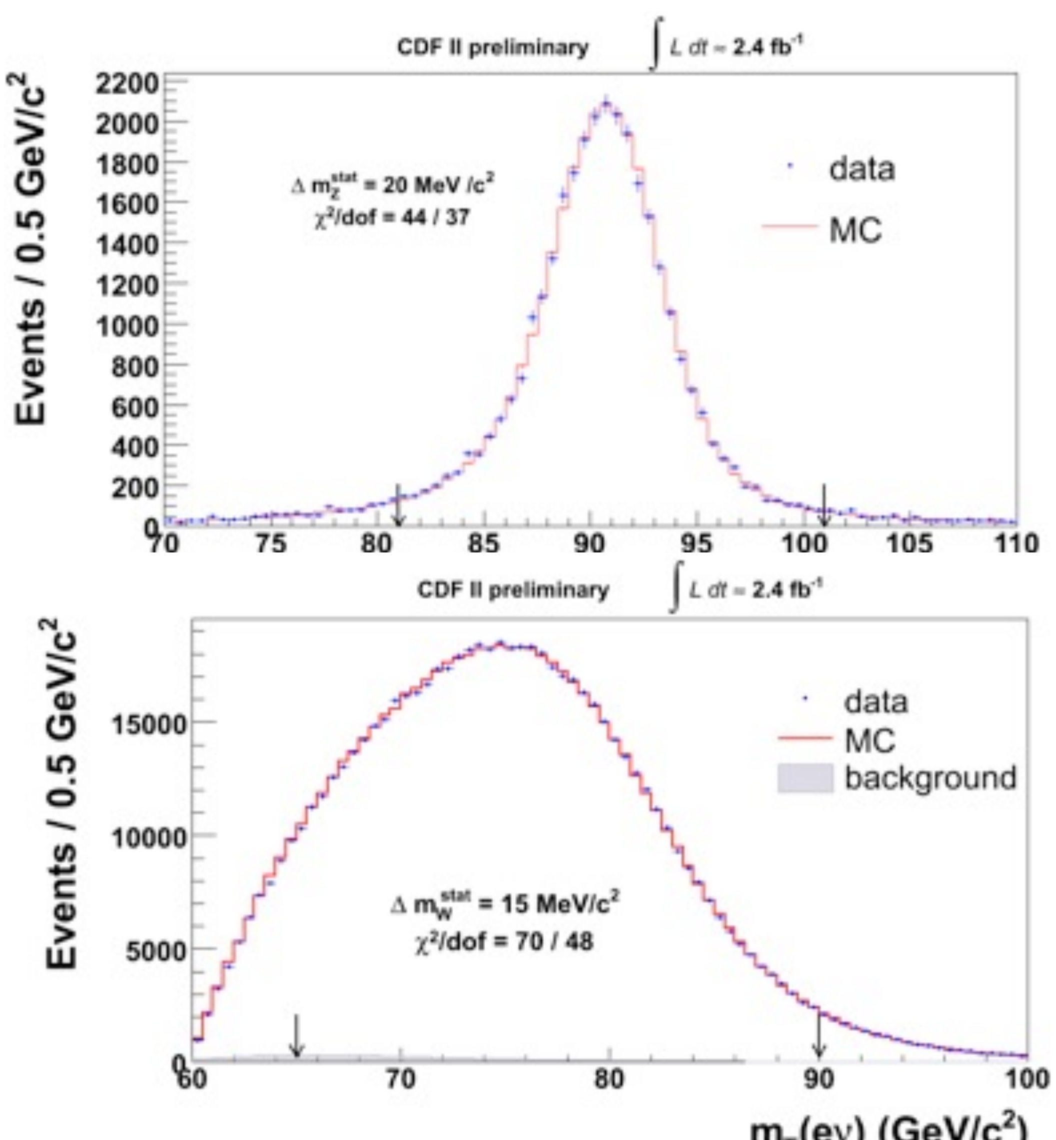
Outline

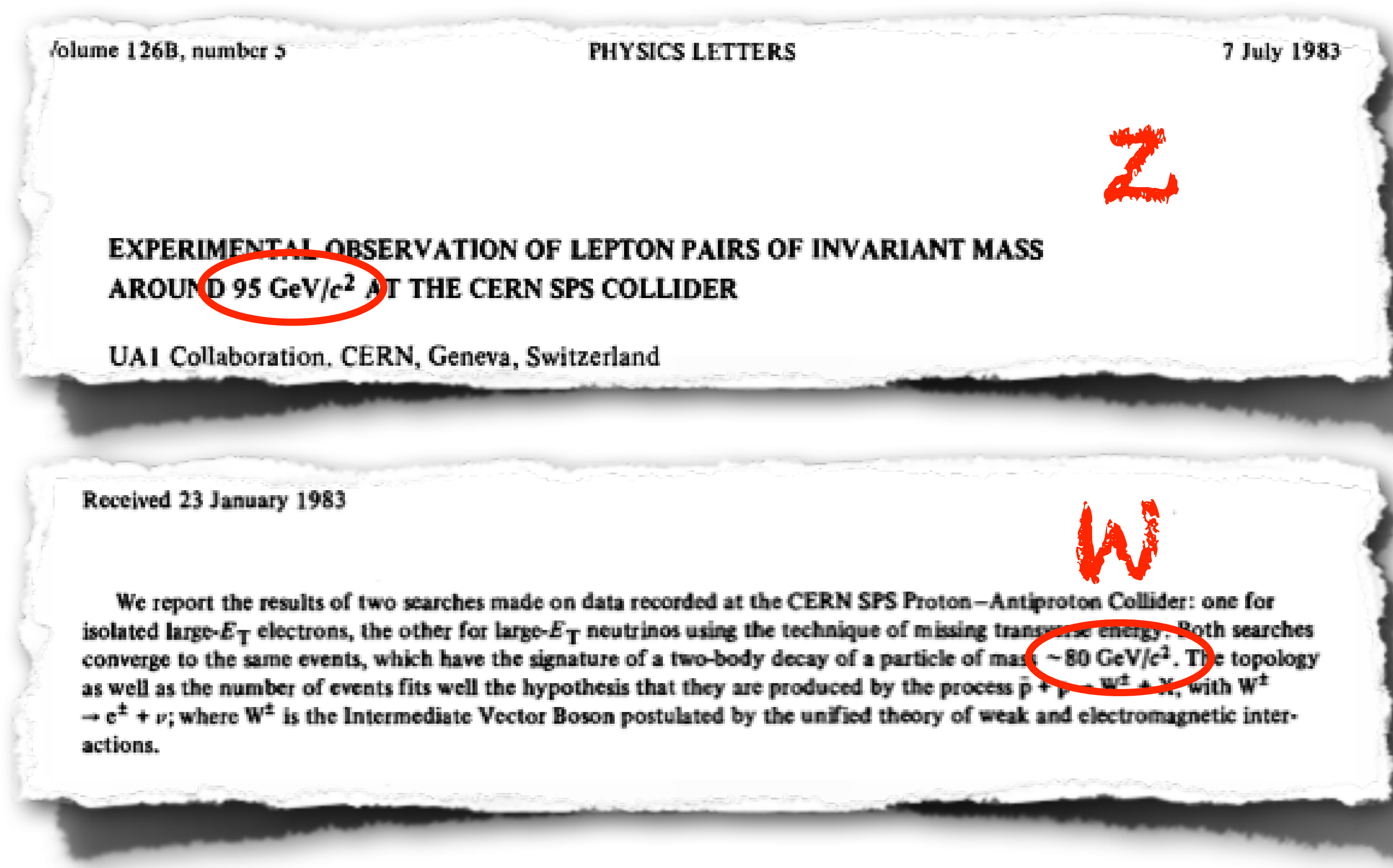
- Motivation for low mass Higgs
- Electrons at CDF
- Adding and modeling electron triggers
- Electron identification neural network
- Bigger picture
- Higgs search outlook



Motivation: We have a mass problem

- The standard model Lagrangian describes massless force carriers
- W & Z bosons are not massless!




Volume 126B, number 5 PHYSICS LETTERS 7 July 1983

Z

EXPERIMENTAL OBSERVATION OF LEPTON PAIRS OF INVARIANT MASS AROUND 95 GeV/c^2 AT THE CERN SPS COLLIDER

UA1 Collaboration, CERN, Geneva, Switzerland

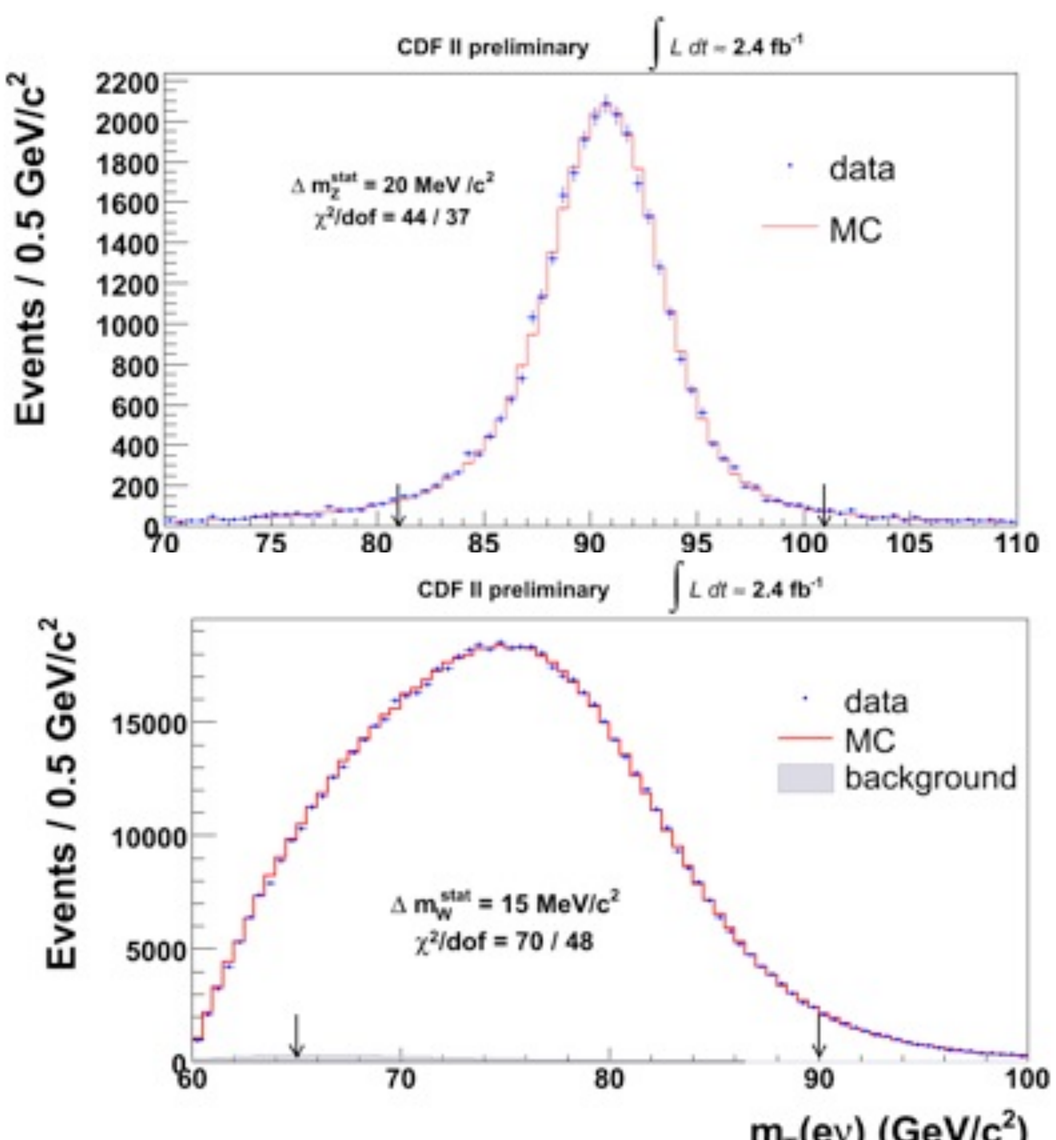
Received 23 January 1983

W

We report the results of two searches made on data recorded at the CERN SPS Proton–Antiproton Collider: one for isolated large-E_T electrons, the other for large-E_T neutrinos using the technique of missing transverse energy. Both searches converge to the same events, which have the signature of a two-body decay of a particle of mass ~80 GeV/c^2. The topology as well as the number of events fits well the hypothesis that they are produced by the process $\bar{p} + p \to W^\pm + X$, with $W^\pm \to e^\pm + \nu$; where $W^\pm$ is the Intermediate Vector Boson postulated by the unified theory of weak and electromagnetic interactions.

Motivation: We have a mass problem

- The standard model Lagrangian describes massless force carriers
- W & Z bosons are not massless!



Volume 126B, number 5 PHYSICS LETTERS 7 July 1983

Z

EXPERIMENTAL OBSERVATION OF LEPTON PAIRS OF INVARIANT MASS AROUND 95 GeV/c^2 AT THE CERN SPS COLLIDER

UA1 Collaboration, CERN, Geneva, Switzerland

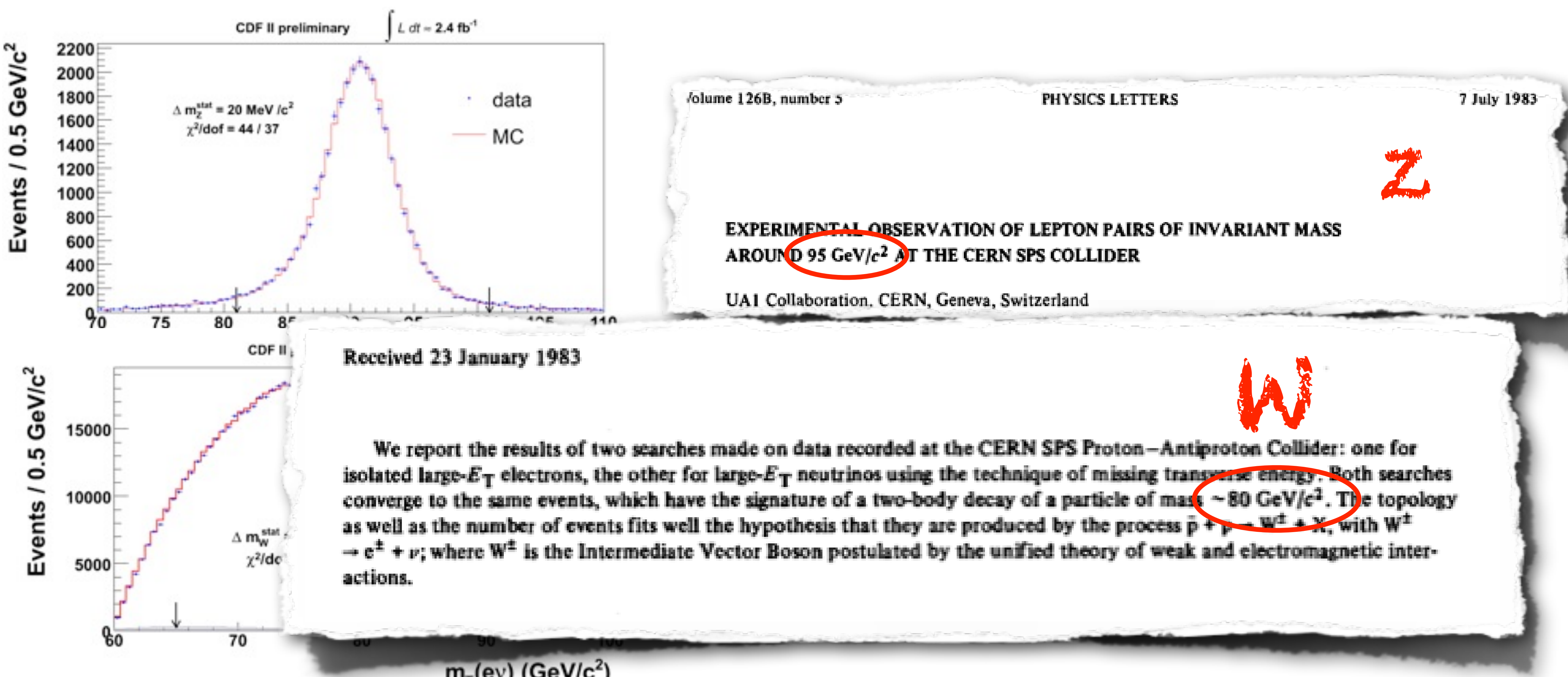
Received 23 January 1983

W

We report the results of two searches made on data recorded at the CERN SPS Proton–Antiproton Collider: one for isolated large-E_T electrons, the other for large-E_T neutrinos using the technique of missing transverse energy. Both searches converge to the same events, which have the signature of a two-body decay of a particle of mass ~80 GeV/c^2. The topology as well as the number of events fits well the hypothesis that they are produced by the process $\bar{p} + p \to W^{\pm} + X$, with $W^{\pm} \to e^{\pm} + \nu$; where $W^{\pm}$ is the Intermediate Vector Boson postulated by the unified theory of weak and electromagnetic interactions.

Motivation: We have a mass problem

- The standard model Lagrangian describes massless force carriers
- W & Z bosons are not massless!



Volume 126B, number 5 PHYSICS LETTERS 7 July 1983

EXPERIMENTAL OBSERVATION OF LEPTON PAIRS OF INVARIANT MASS AROUND 95 GeV/c^2 AT THE CERN SPS COLLIDER

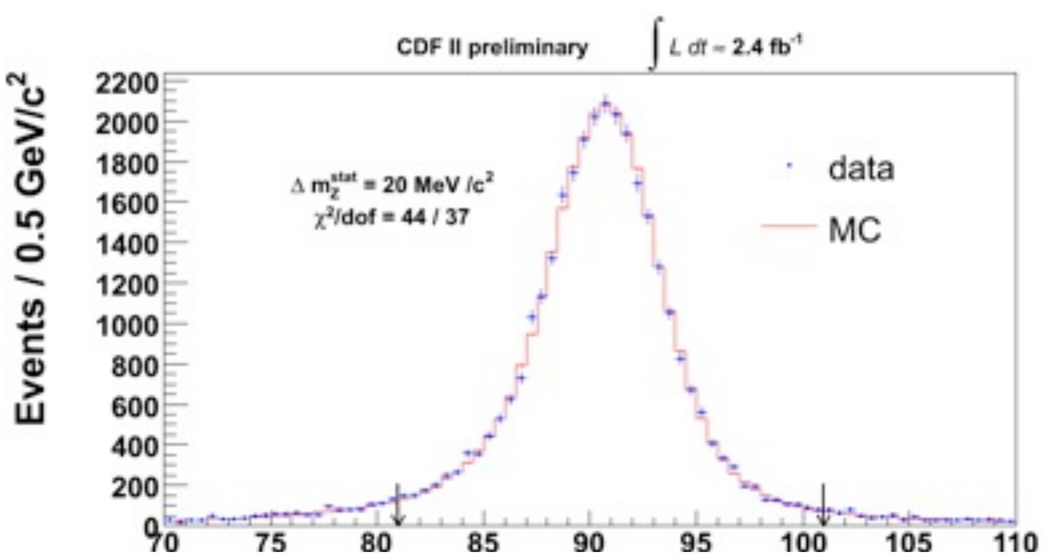
UA1 Collaboration, CERN, Geneva, Switzerland

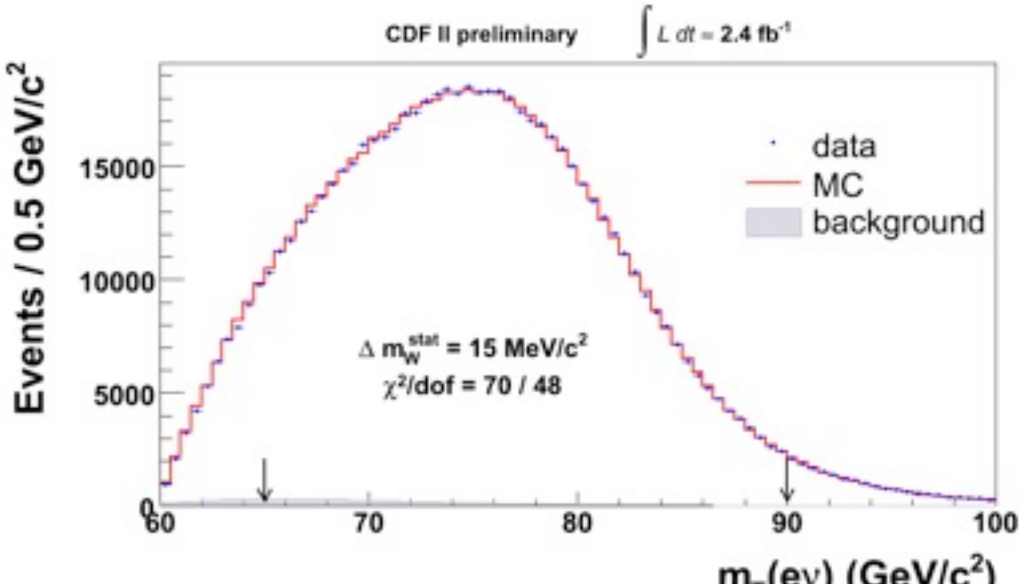
Received 23 January 1983

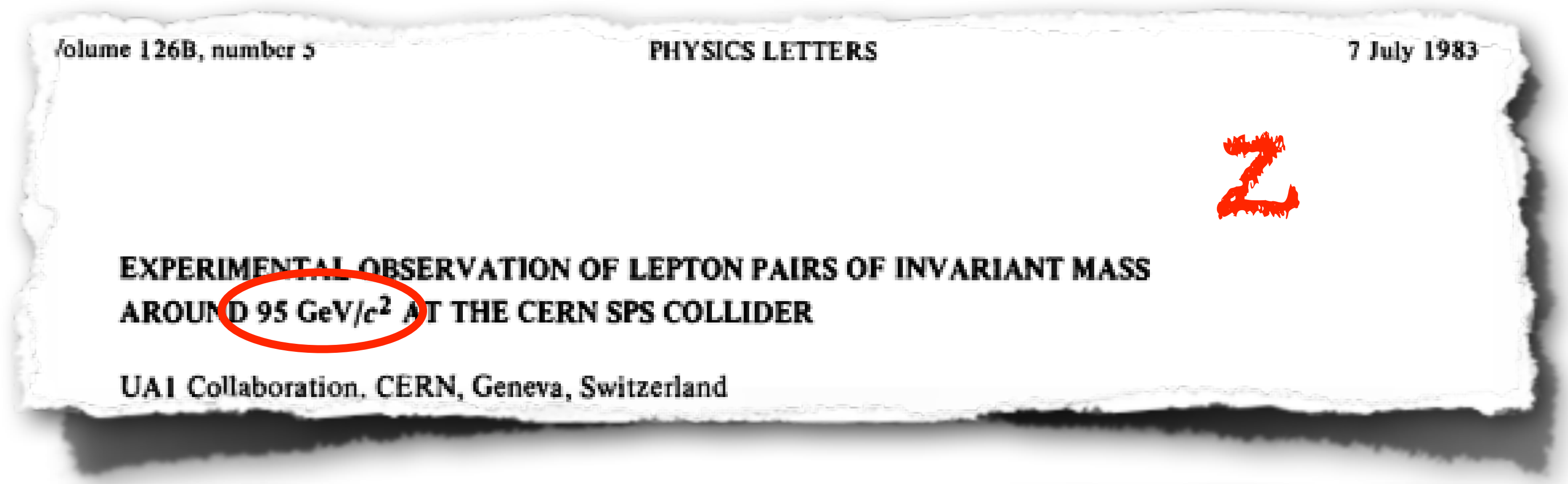
We report the results of two searches made on data recorded at the CERN SPS Proton–Antiproton Collider: one for isolated large-E_T electrons, the other for large-E_T neutrinos using the technique of missing transverse energy. Both searches converge to the same events, which have the signature of a two-body decay of a particle of mass ~80 GeV/c^2. The topology as well as the number of events fits well the hypothesis that they are produced by the process $\bar{p} + p \to W^{\pm} + X$, with $W^{\pm} \to e^{\pm} + \nu$; where $W^{\pm}$ is the Intermediate Vector Boson postulated by the unified theory of weak and electromagnetic interactions.

Motivation: We have a mass problem

- The standard model Lagrangian describes massless force carriers
- W & Z bosons are not massless!



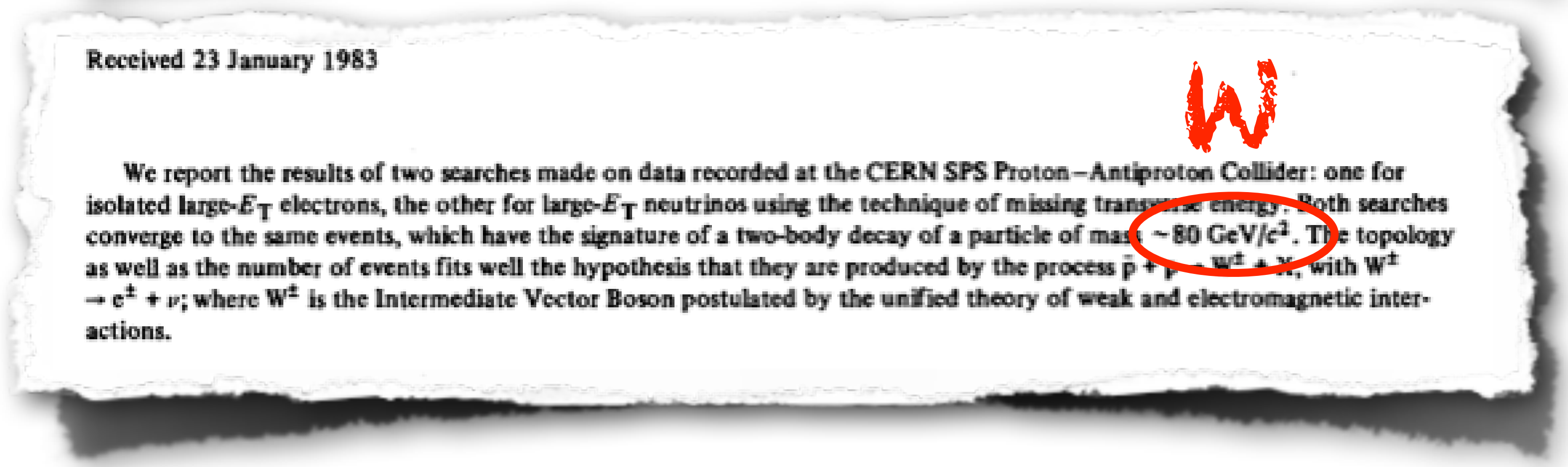




Volume 126B, number 5 PHYSICS LETTERS 7 July 1983

EXPERIMENTAL OBSERVATION OF LEPTON PAIRS OF INVARIANT MASS AROUND 95 GeV/c^2 AT THE CERN SPS COLLIDER

UA1 Collaboration, CERN, Geneva, Switzerland



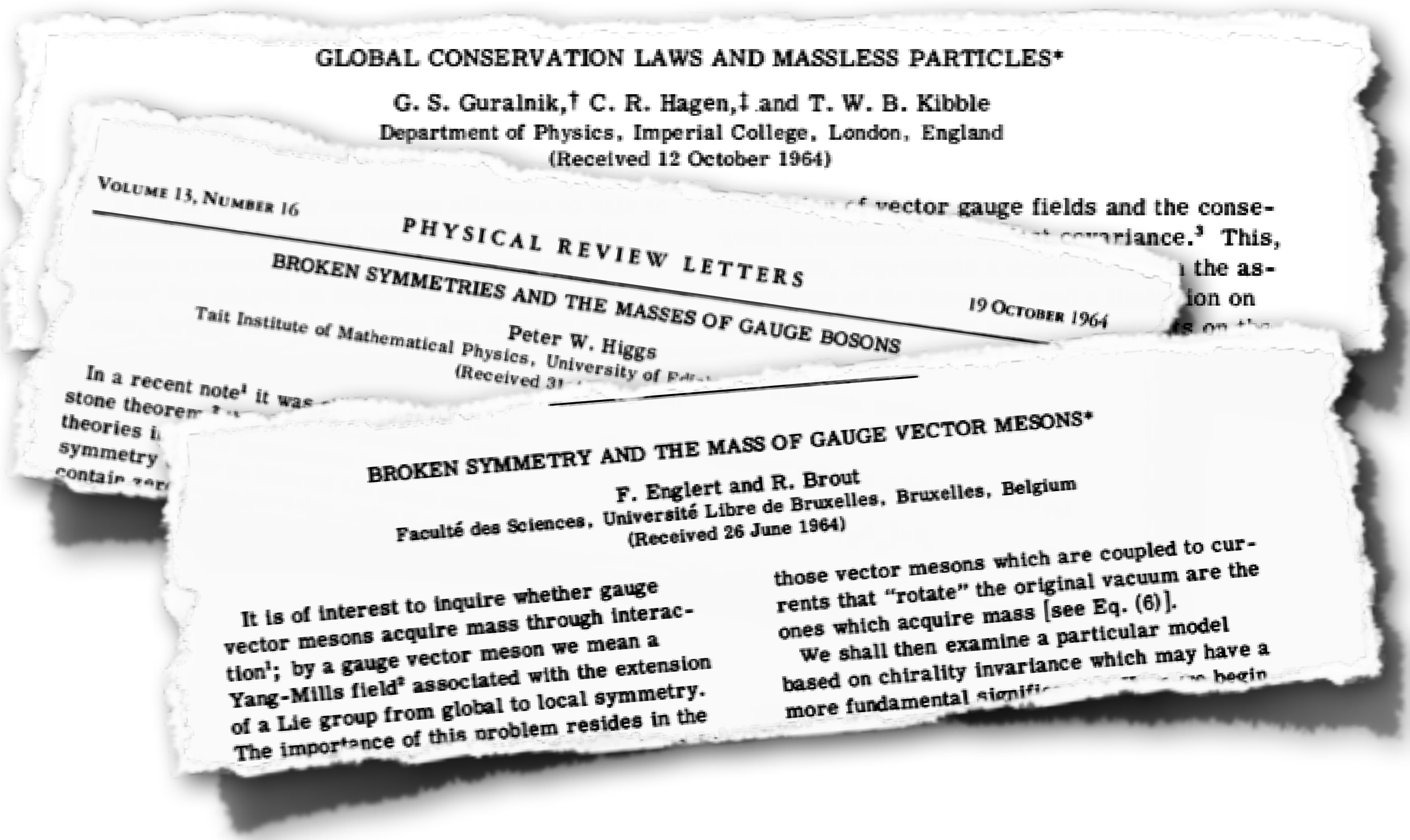
Received 23 January 1983

We report the results of two searches made on data recorded at the CERN SPS Proton–Antiproton Collider: one for isolated large-E_T electrons, the other for large-E_T neutrinos using the technique of missing transverse energy. Both searches converge to the same events, which have the signature of a two-body decay of a particle of mass ~80 GeV/c^2. The topology as well as the number of events fits well the hypothesis that they are produced by the process $\bar{p} + p \to W^\pm + X$, with $W^\pm \to e^\pm + \nu$; where $W^\pm$ is the Intermediate Vector Boson postulated by the unified theory of weak and electromagnetic interactions.

Proposed Solution: Higgs boson

Proposed Solution: Higgs boson

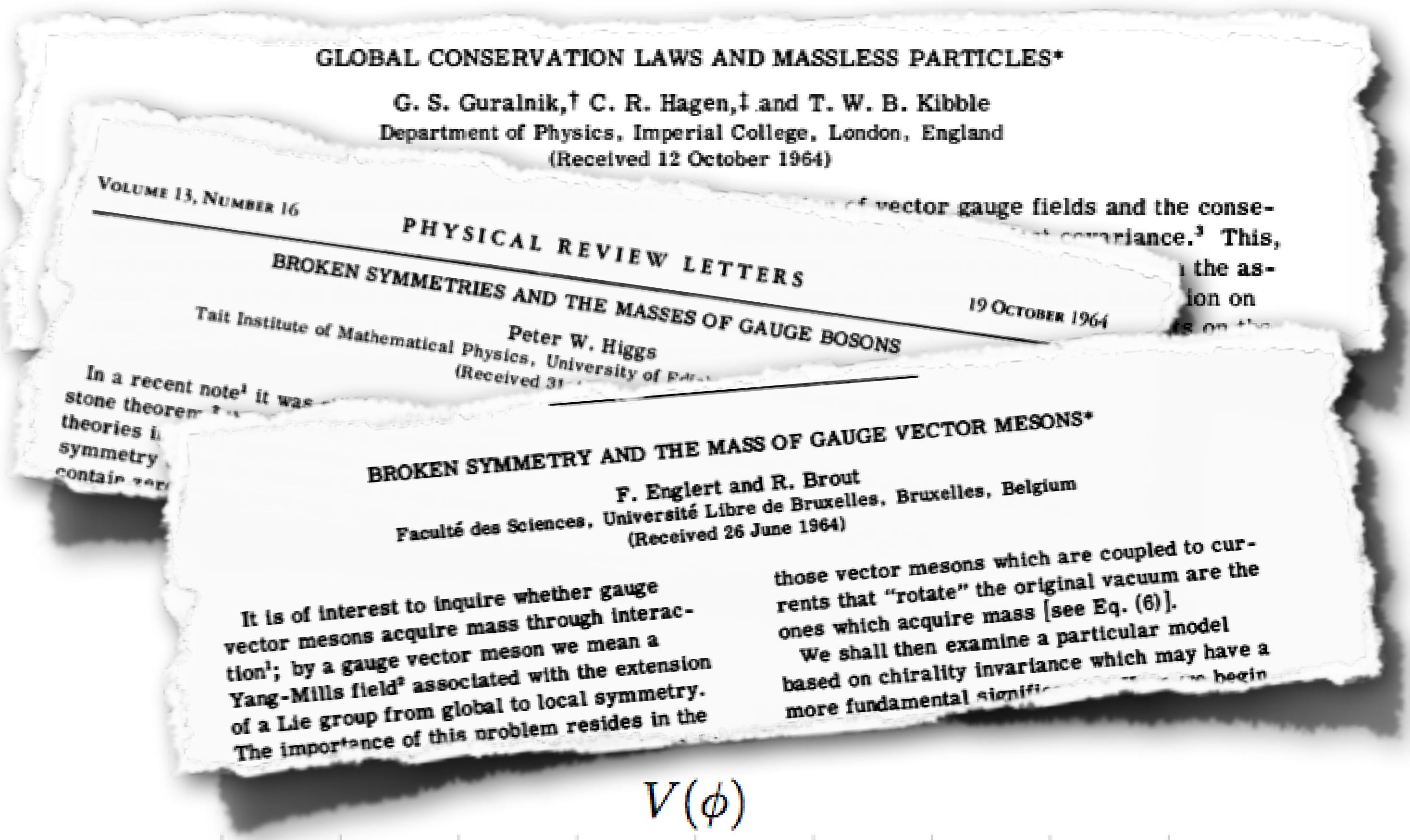
- In the 1960s, Brout, Englert, Higgs, Kibble, Guralnik and Hagen devised a method for electroweak symmetry breaking



Proposed Solution: Higgs boson

- In the 1960s, Brout, Englert, Higgs, Kibble, Guralnik and Hagen devised a method for electroweak symmetry breaking

- Method introduced a potential that spontaneously broke the symmetry



GLOBAL CONSERVATION LAWS AND MASSLESS PARTICLES*

G. S. Guralnik,† C. R. Hagen,‡ and T. W. B. Kibble
Department of Physics, Imperial College, London, England
(Received 12 October 1964)

VOLUME 13, NUMBER 16 PHYSICAL REVIEW LETTERS 19 OCTOBER 1964

BROKEN SYMMETRIES AND THE MASSES OF GAUGE BOSONS

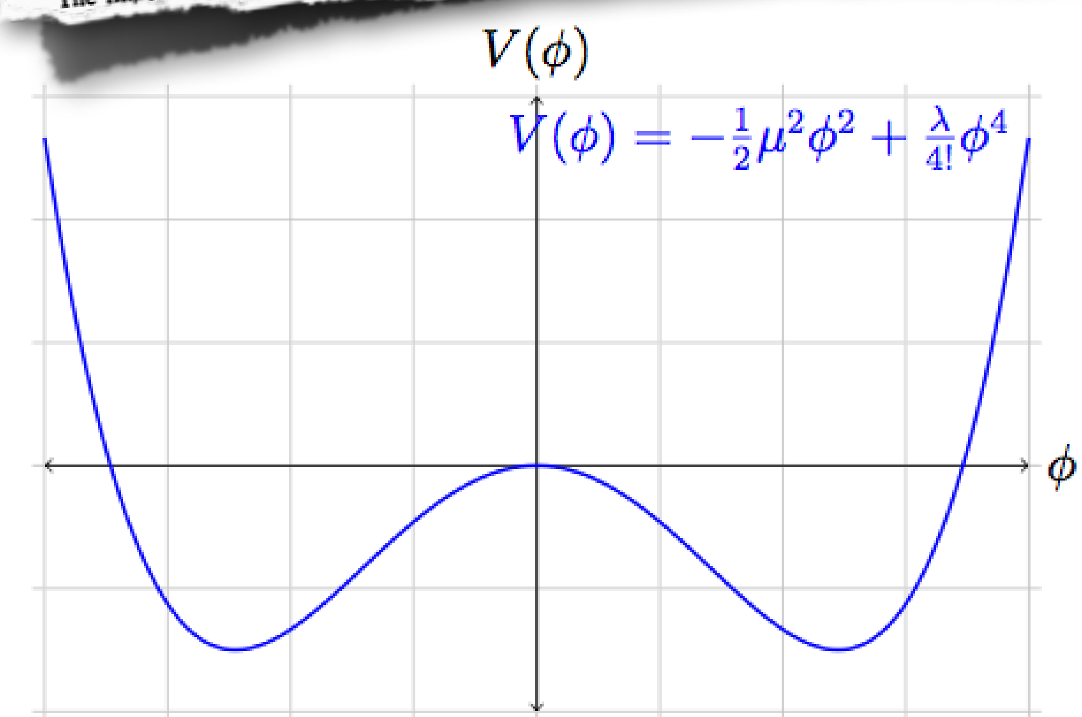
Peter W. Higgs
Tait Institute of Mathematical Physics, University of

BROKEN SYMMETRY AND THE MASS OF GAUGE VECTOR MESONS*

F. Englert and R. Brout
Faculté des Sciences, Université Libre de Bruxelles, Bruxelles, Belgium
(Received 26 June 1964)

It is of interest to inquire whether gauge vector mesons acquire mass through interaction[1]; by a gauge vector meson we mean a Yang-Mills field[2] associated with the extension of a Lie group from global to local symmetry. The importance of this problem resides in the

those vector mesons which are coupled to currents that "rotate" the original vacuum are the ones which acquire mass [see Eq. (6)].
We shall then examine a particular model based on chirality invariance which may have a more fundamental



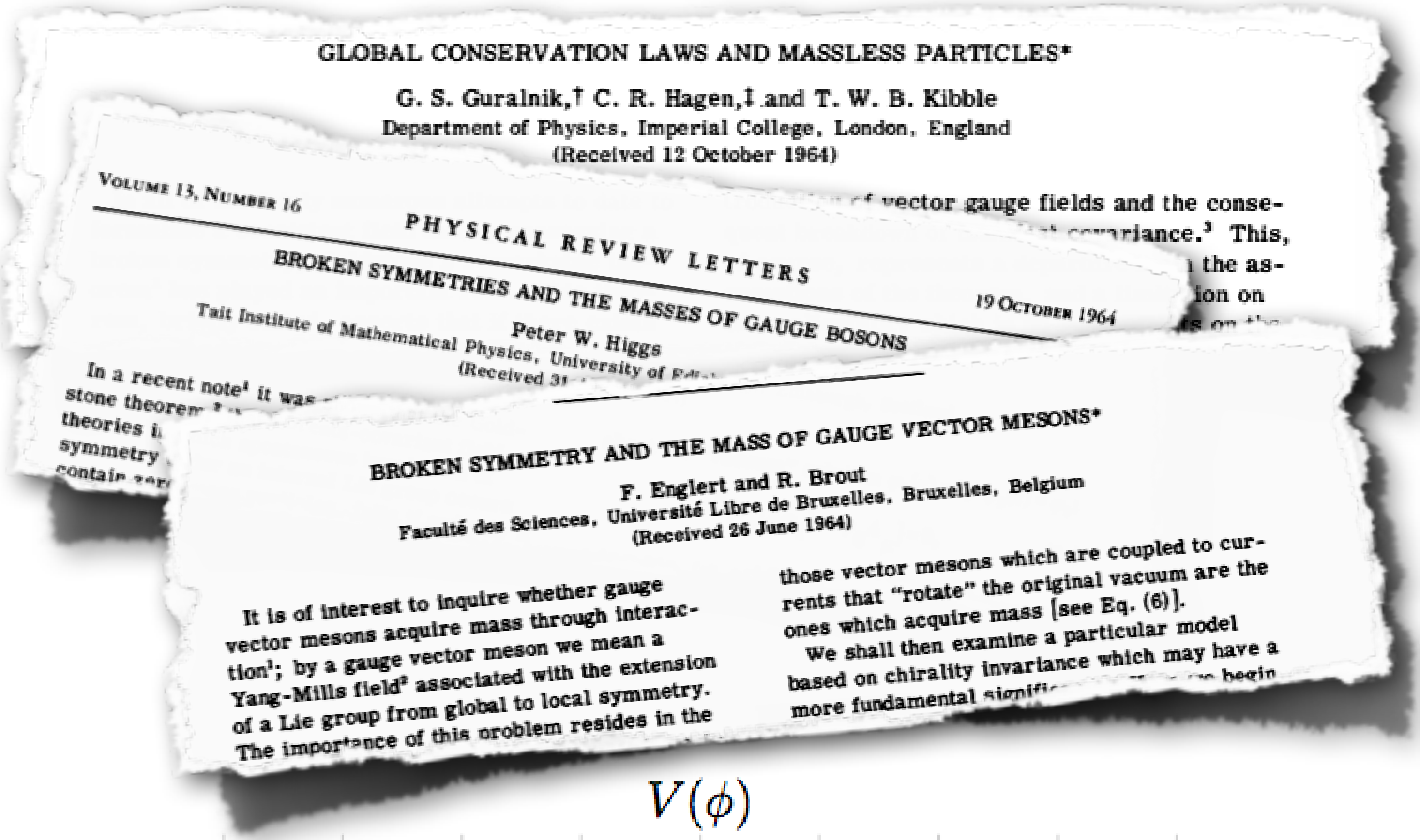
Proposed Solution: Higgs boson

- In the 1960s, Brout, Englert, Higgs, Kibble, Guralnik and Hagen devised a method for electroweak symmetry breaking

- Method introduced a potential that spontaneously broke the symmetry

- The consequence of this was a new particle -- the Higgs boson -- a physically realizable particle

- However, it does not predict the mass!

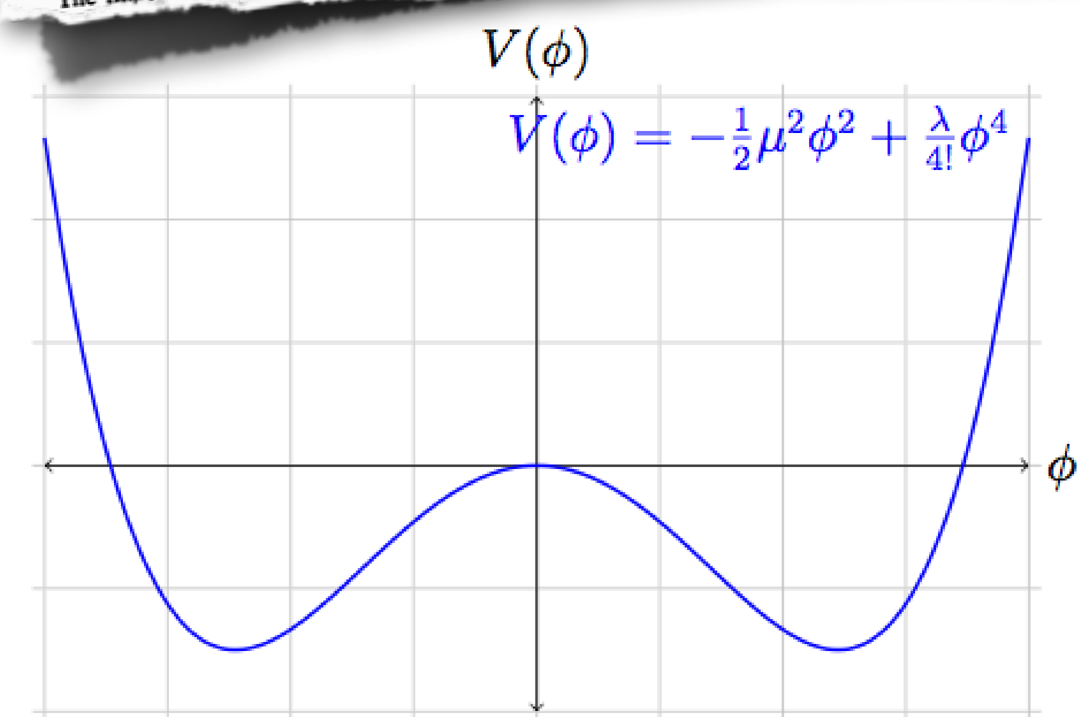

GLOBAL CONSERVATION LAWS AND MASSLESS PARTICLES*
G. S. Guralnik,† C. R. Hagen,‡ and T. W. B. Kibble
Department of Physics, Imperial College, London, England
(Received 12 October 1964)

VOLUME 13, NUMBER 16 PHYSICAL REVIEW LETTERS 19 OCTOBER 1964
BROKEN SYMMETRIES AND THE MASSES OF GAUGE BOSONS
Peter W. Higgs
Tait Institute of Mathematical Physics, University of

BROKEN SYMMETRY AND THE MASS OF GAUGE VECTOR MESONS*
F. Englert and R. Brout
Faculté des Sciences, Université Libre de Bruxelles, Bruxelles, Belgium
(Received 26 June 1964)

It is of interest to inquire whether gauge vector mesons acquire mass through interaction[1]; by a gauge vector meson we mean a Yang-Mills field[2] associated with the extension of a Lie group from global to local symmetry.

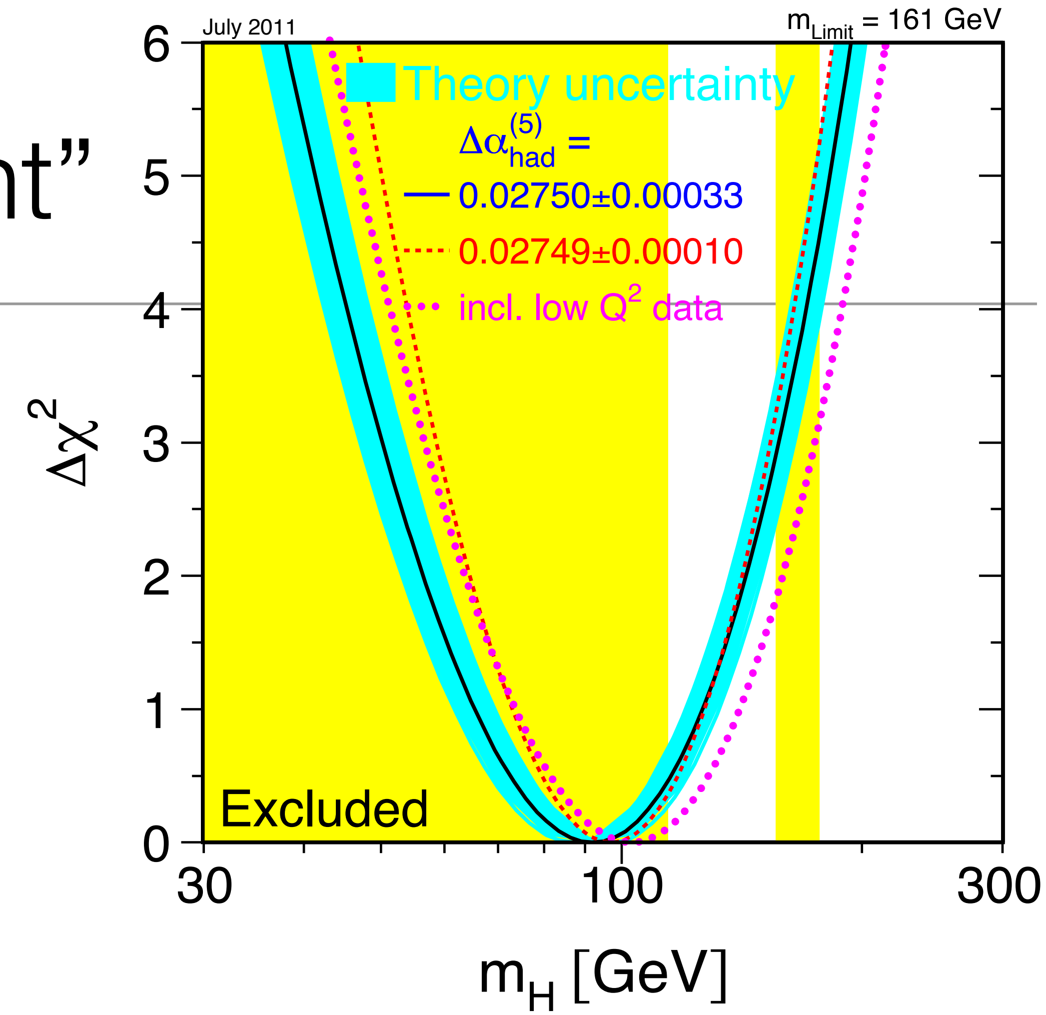
those vector mesons which are coupled to currents that "rotate" the original vacuum are the ones which acquire mass [see Eq. (6)].
We shall then examine a particular model based on chirality invariance which may have a more fundamental



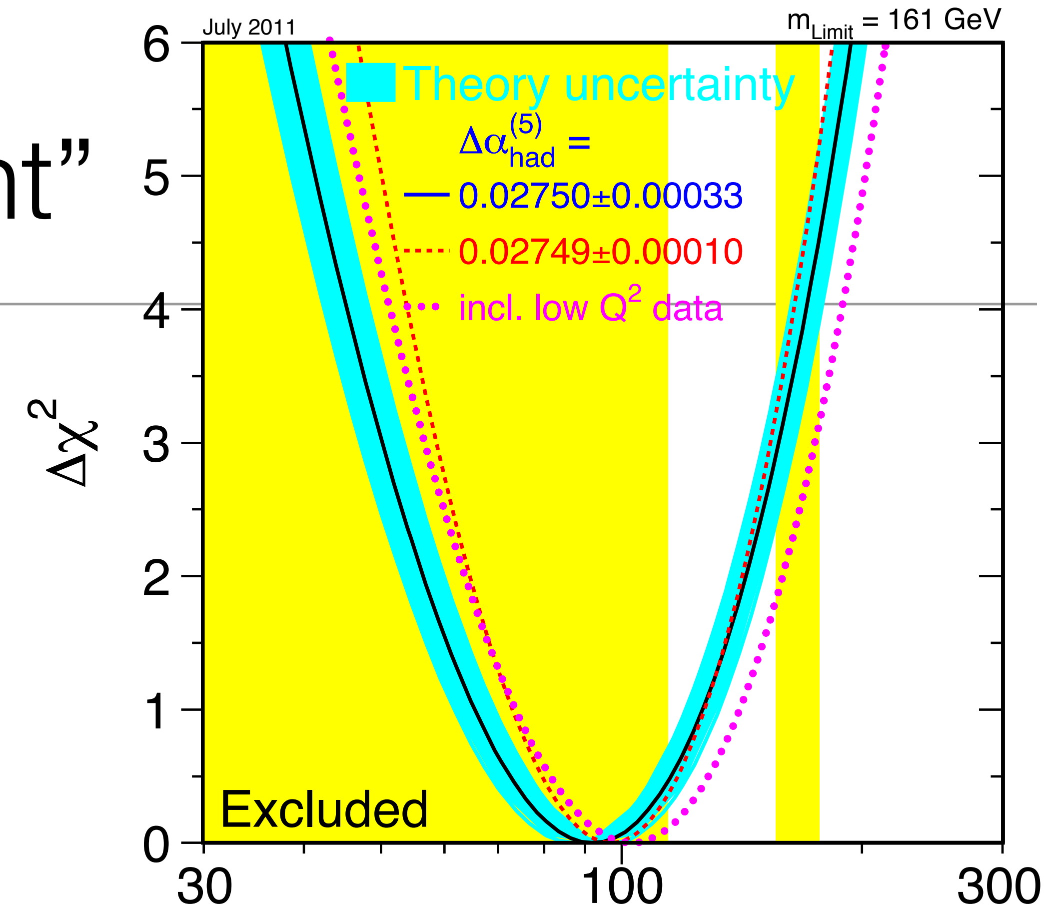
Searching for the Higgs --
Why the Higgs should be “light”

Searching for the Higgs -- Why the Higgs should be "light"

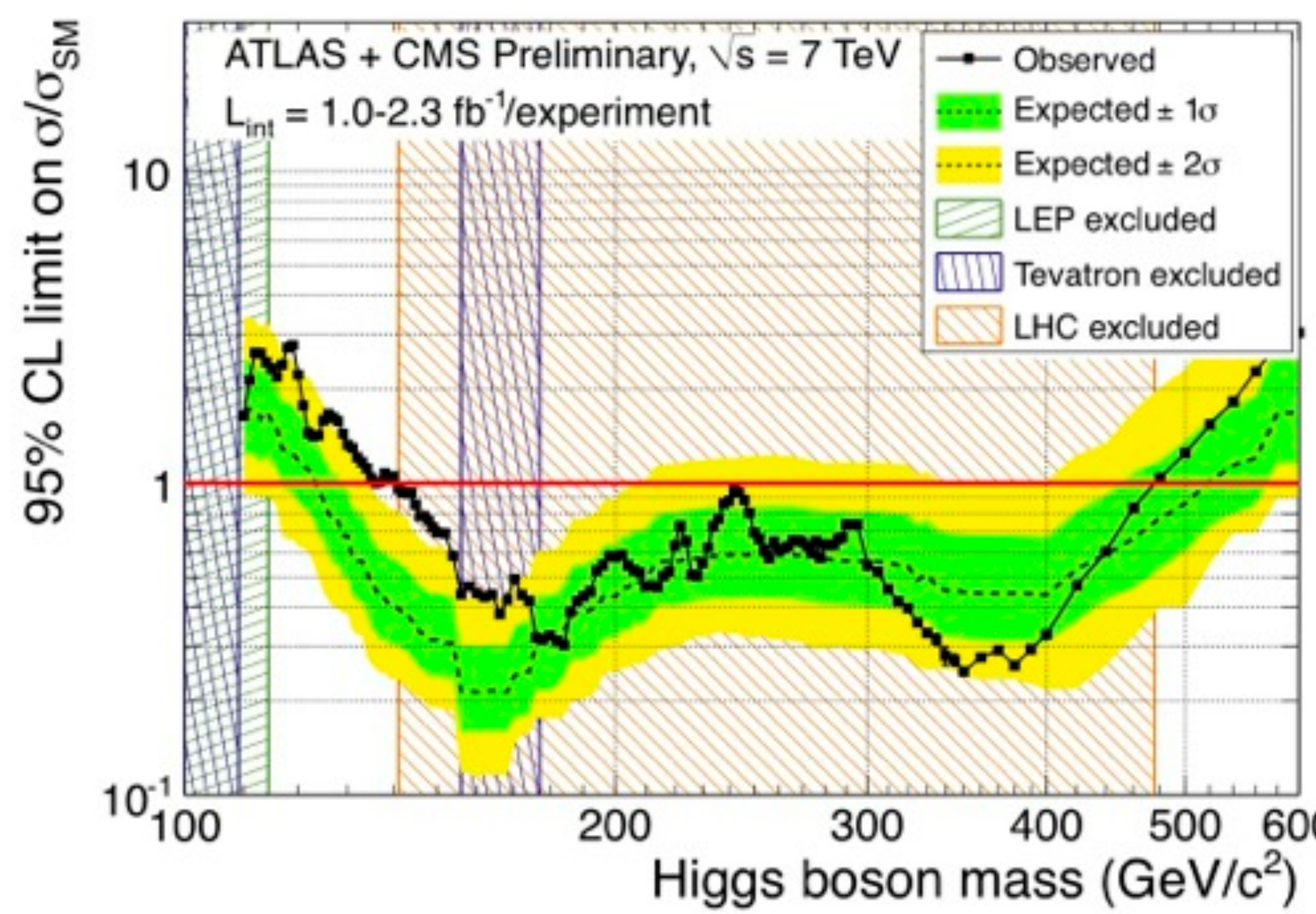
- Previous searches ruled out up to 114.4 GeV/c^2 at the 95% CL (LEP result)
- Precision electroweak data predict a mass around 92^{+34}_{-26} GeV/c^2



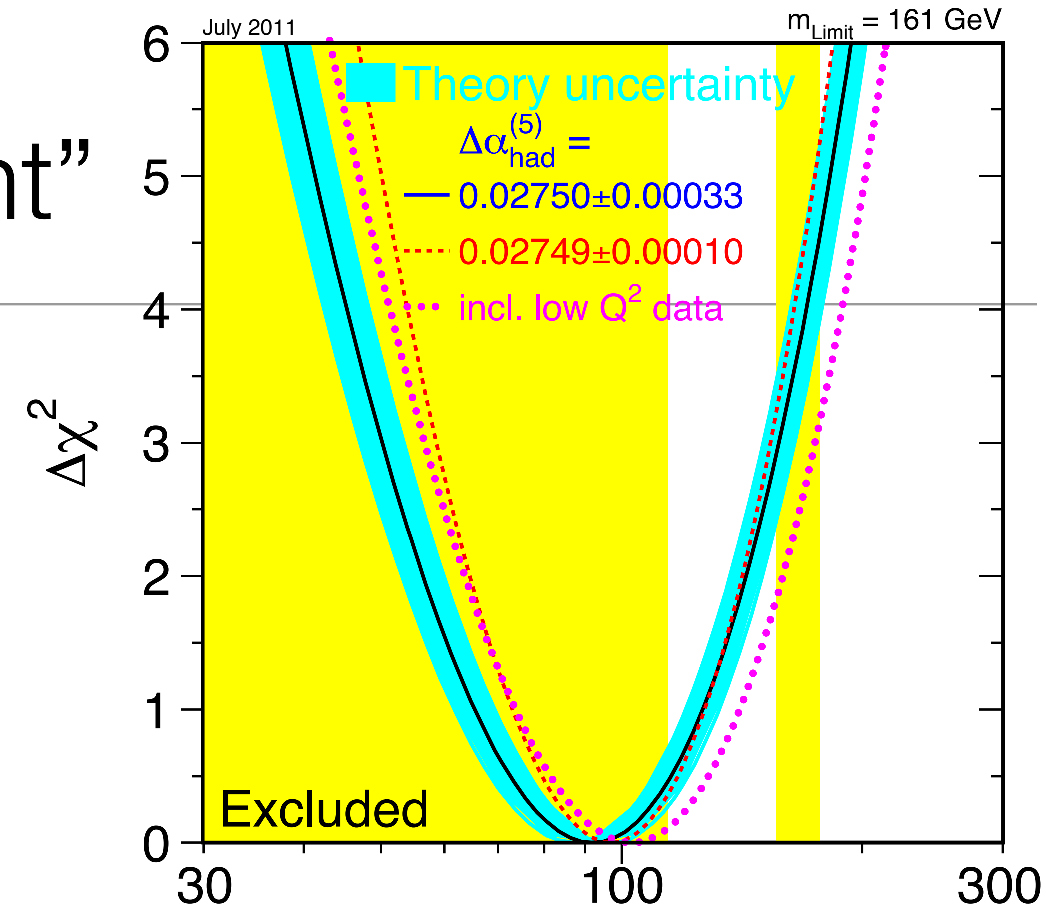
Searching for the Higgs -- Why the Higgs should be “light”



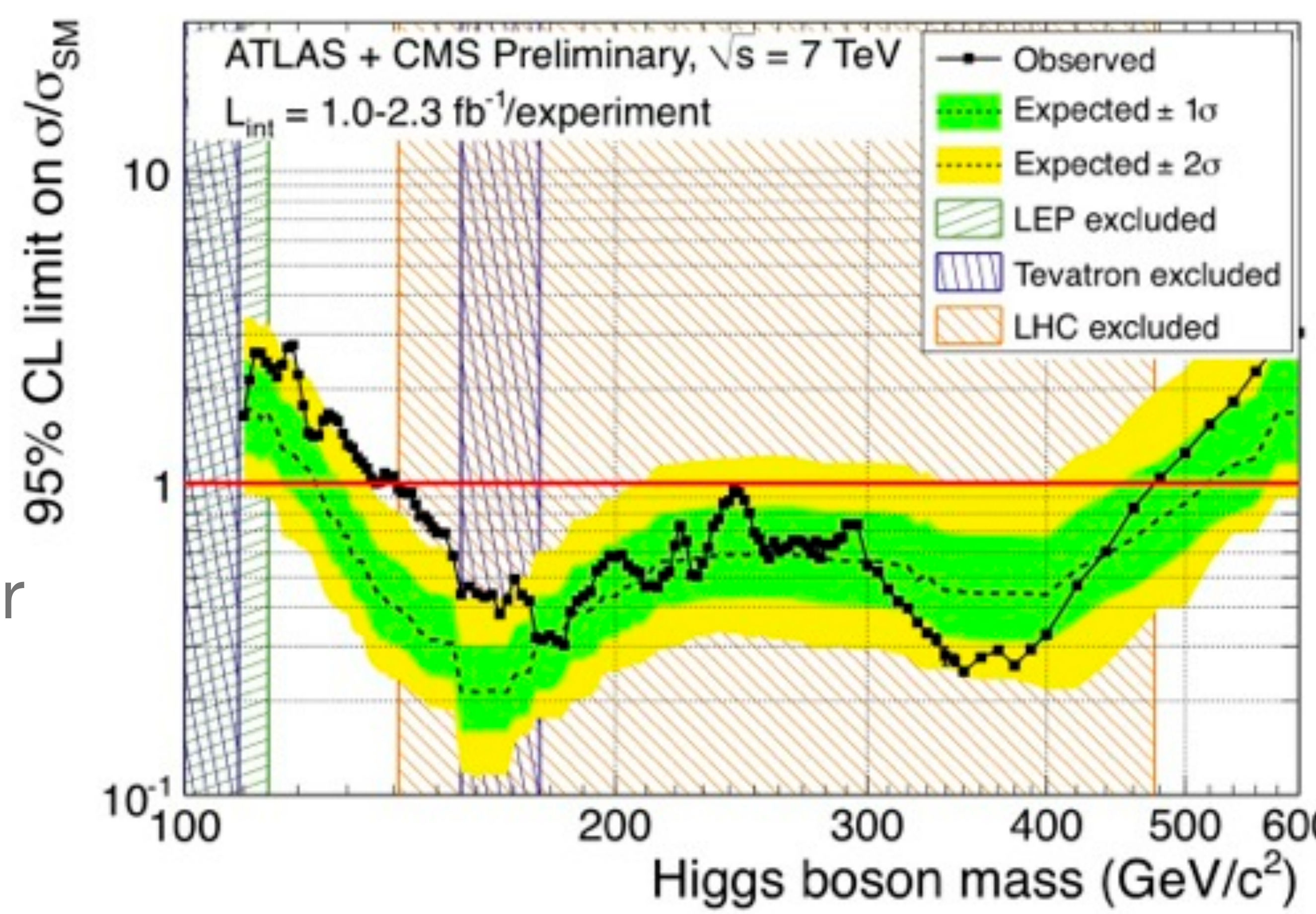
- Previous searches ruled out up to 114.4 GeV/c^2 at the 95% CL (LEP result)
- Precision electroweak data predict a mass around 92^{+34}_{-26} GeV/c^2
- Hadron Collider Searches
  - TeV
  - LHC
- So we focus in the “light” region 100-150 GeV/c^2



Searching for the Higgs -- Why the Higgs should be "light"



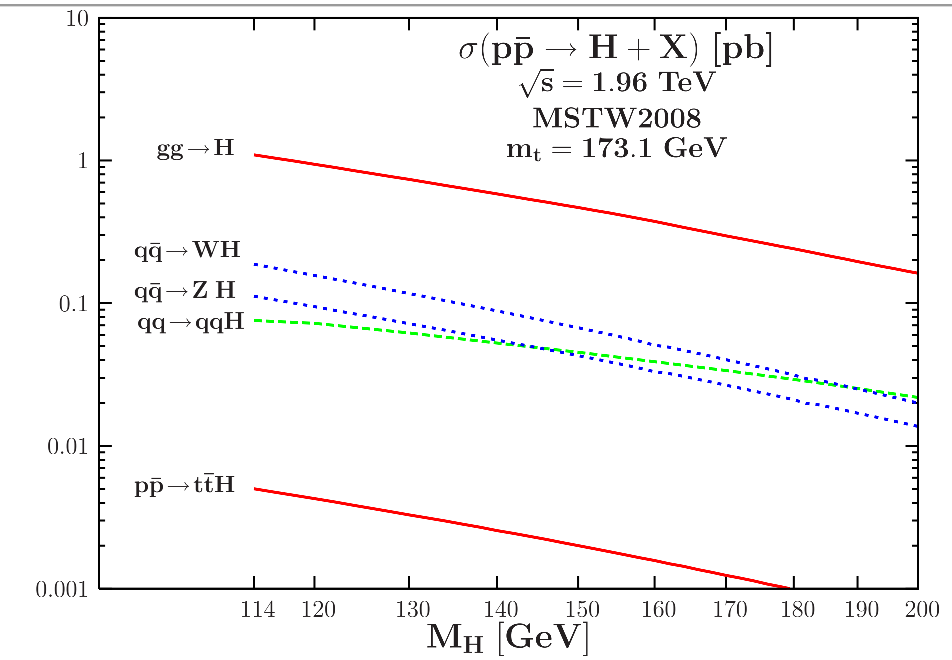
- Previous searches ruled out up to 114.4 GeV/c^2 at the 95% CL (LEP result)
- Precision electroweak data predict a mass around 92^{+34}_{-26} GeV/c^2
- Hadron Collider Searches
    - TeV
    - LHC
- So we focus in the "light" region 100-150 GeV/c^2
    - Recent results from LHC further motivate between 115-130 GeV/c^2

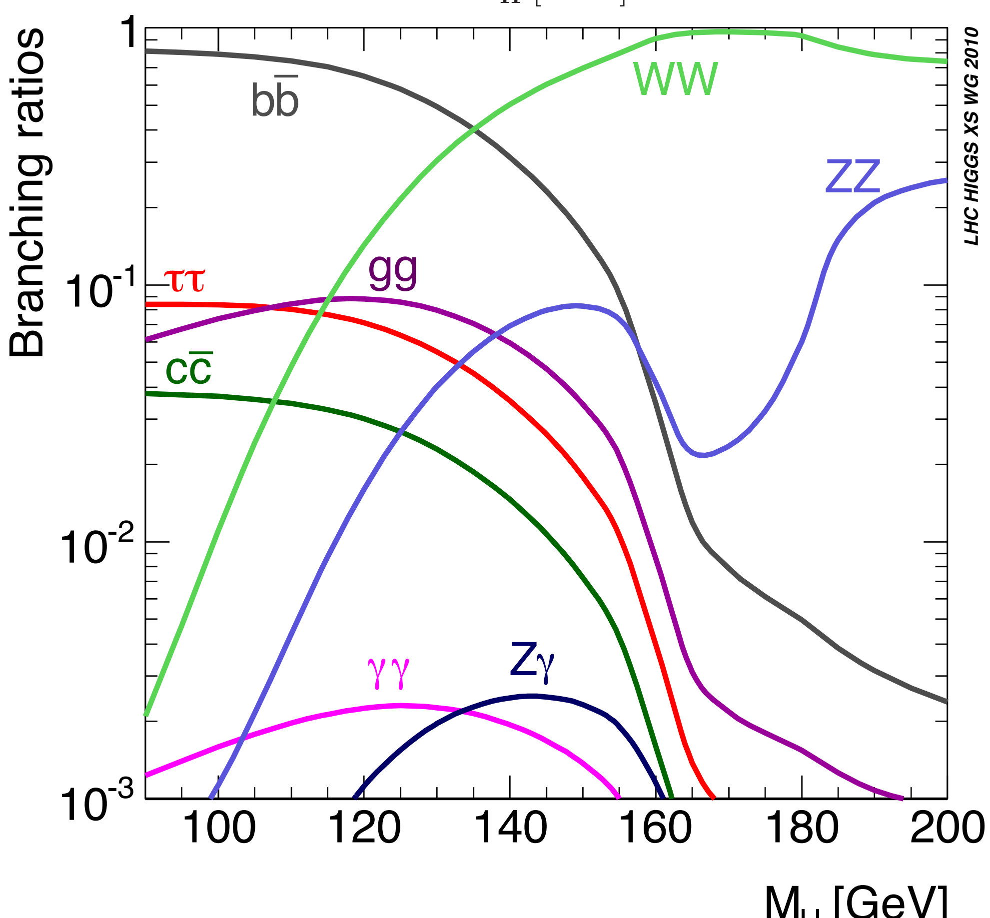


Looking into the Light Region

Looking into the Light Region

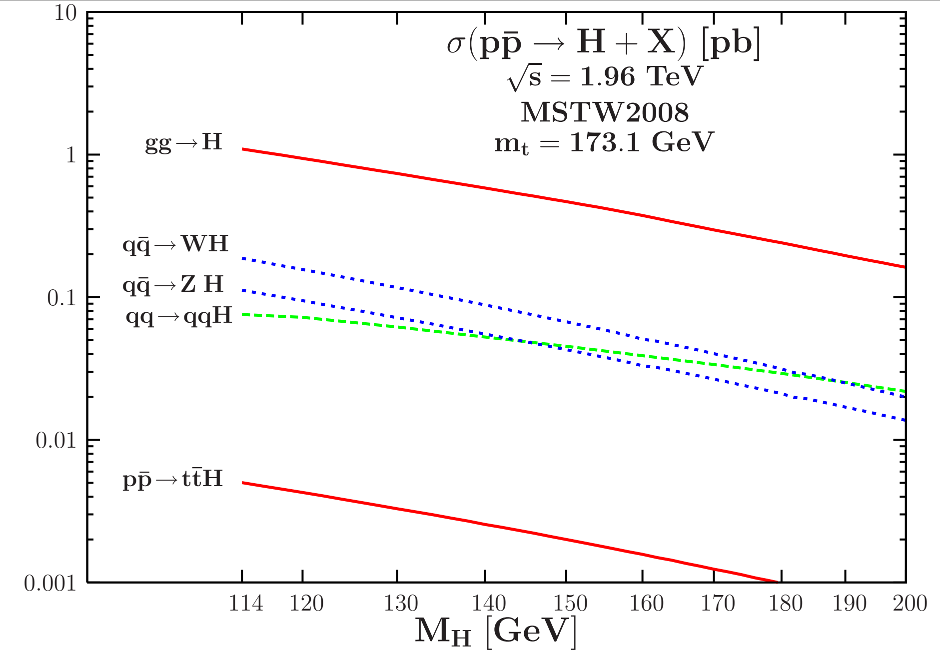
- There are multiple production and decay modes

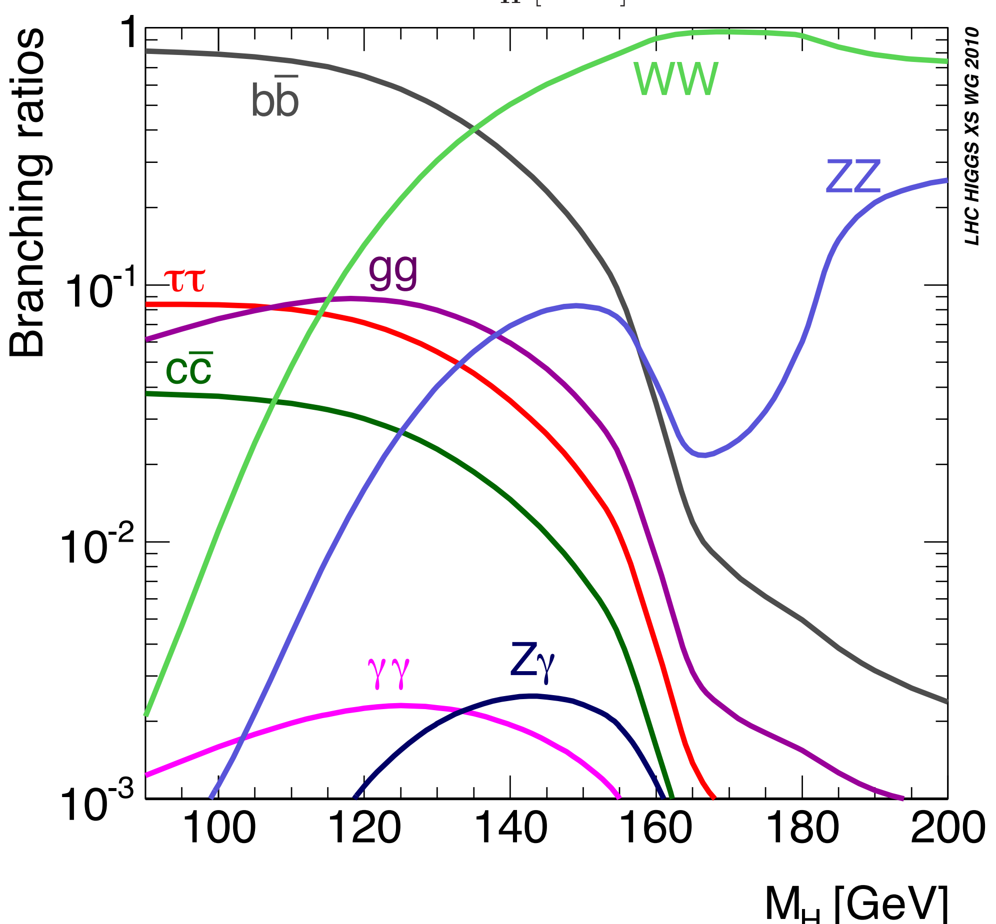




Looking into the Light Region

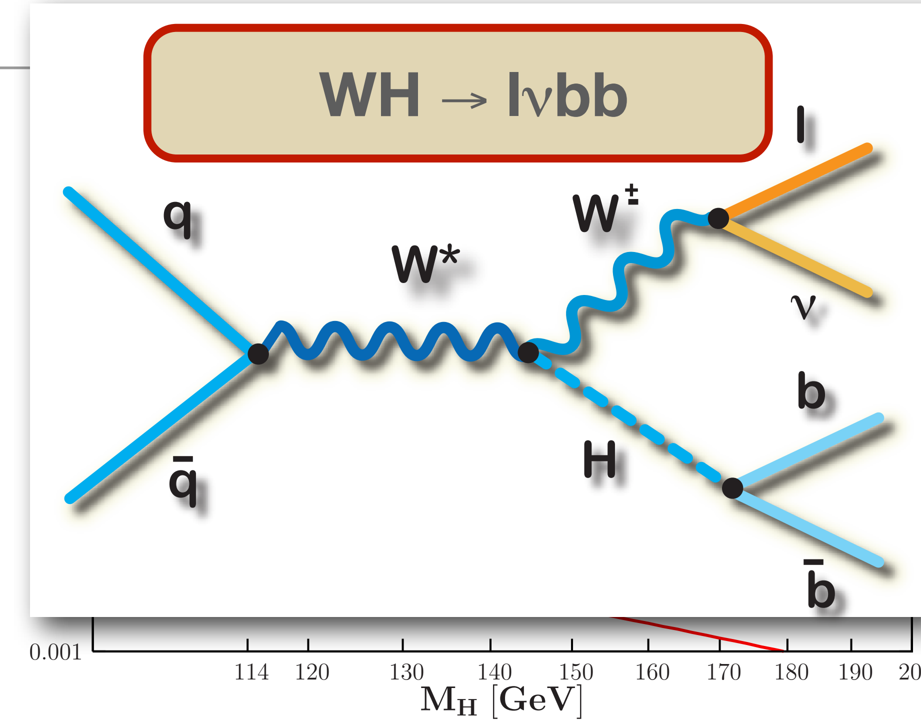
- There are multiple production and decay modes
- WH & ZH (H to bb) are dominant contributors (≲135 GeV/c^2) (H to bb is dominated by background)

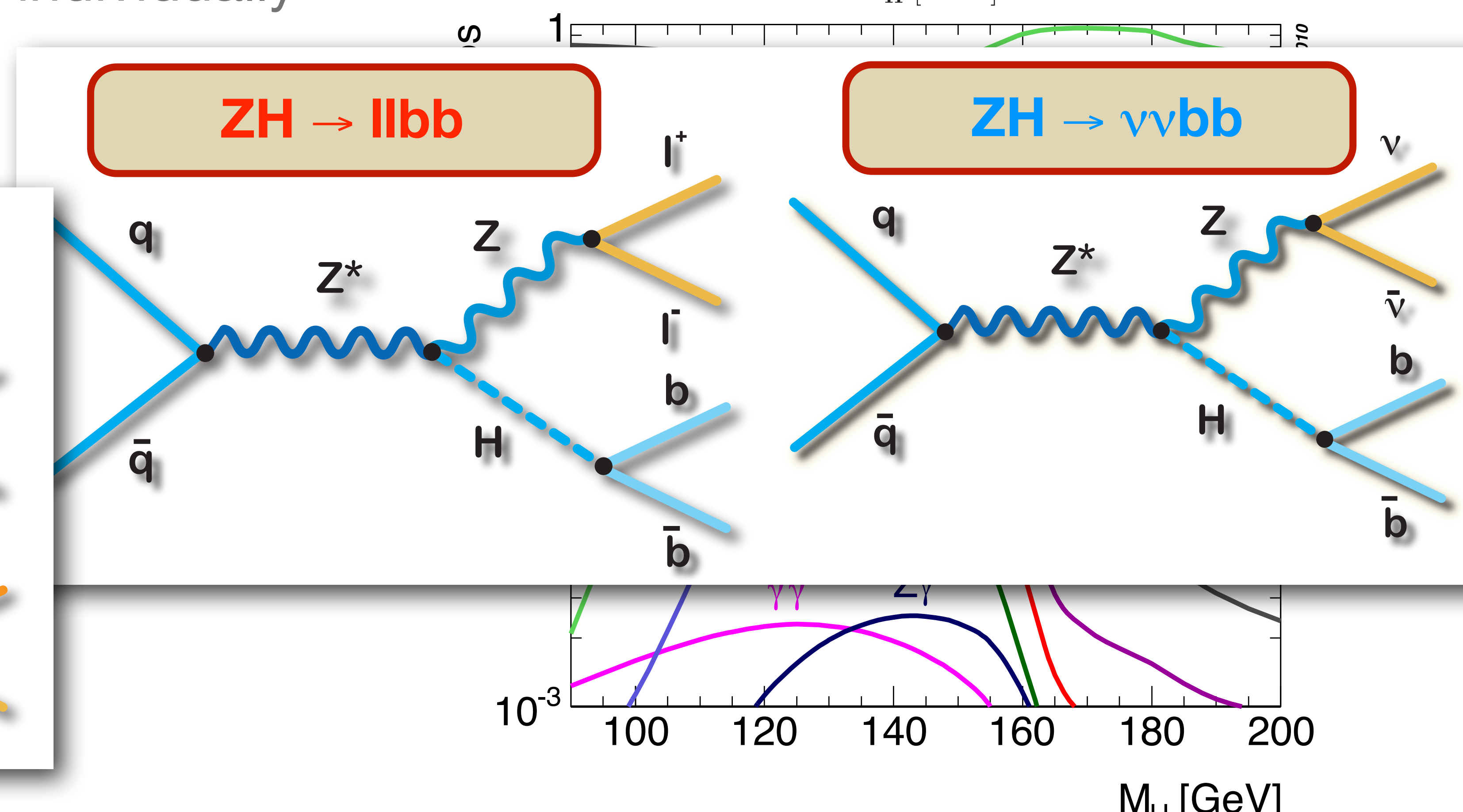


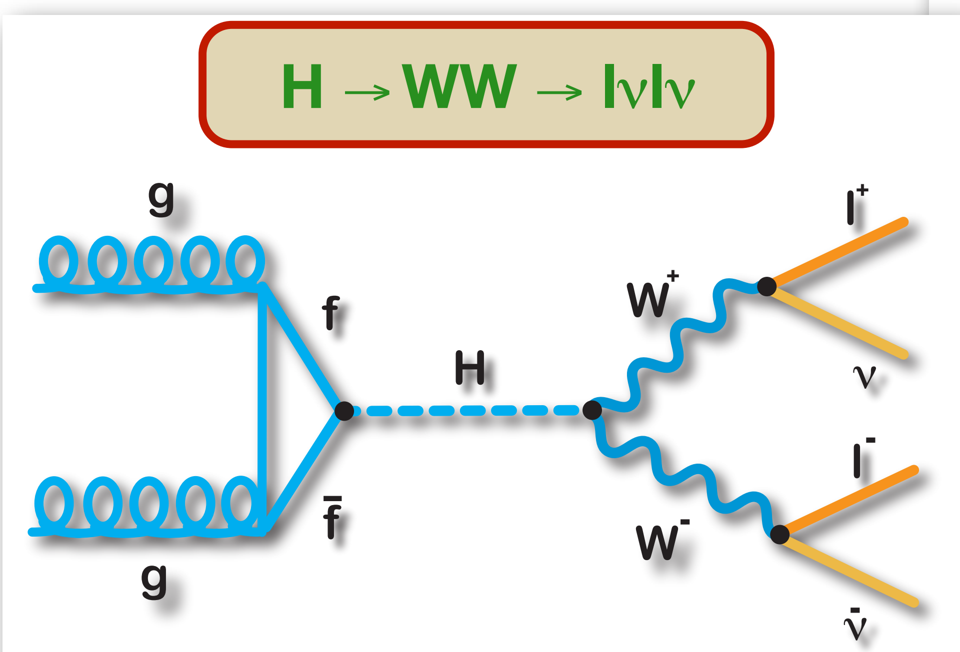


Looking into the Light Region

- There are multiple production and decay modes
- WH & ZH (H to bb) are dominant contributors (≲135 GeV/c^2) (H to bb is dominated by background)
- These channels are analyzed individually ("optimized" analyses)

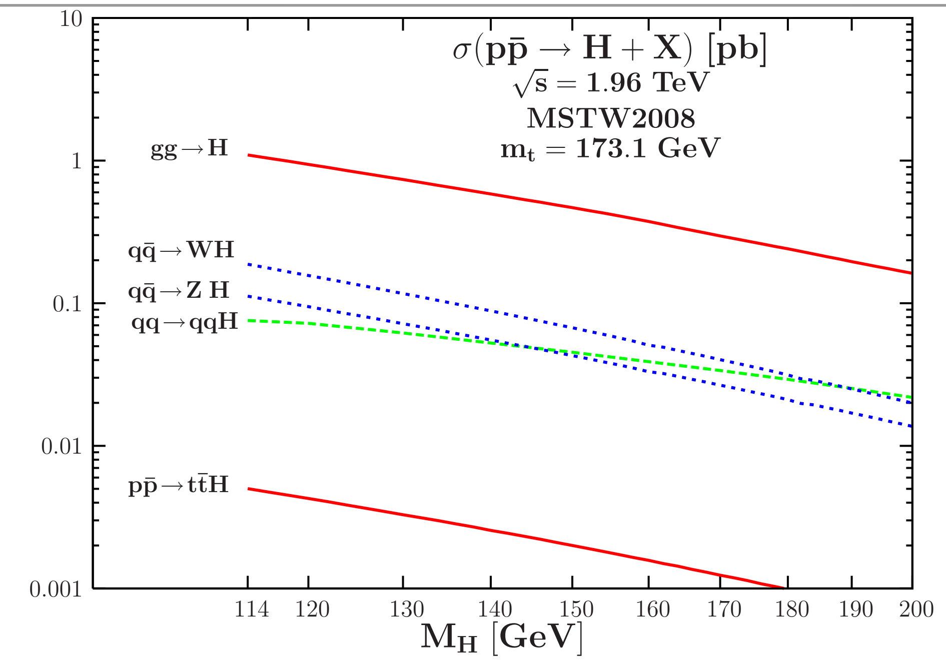


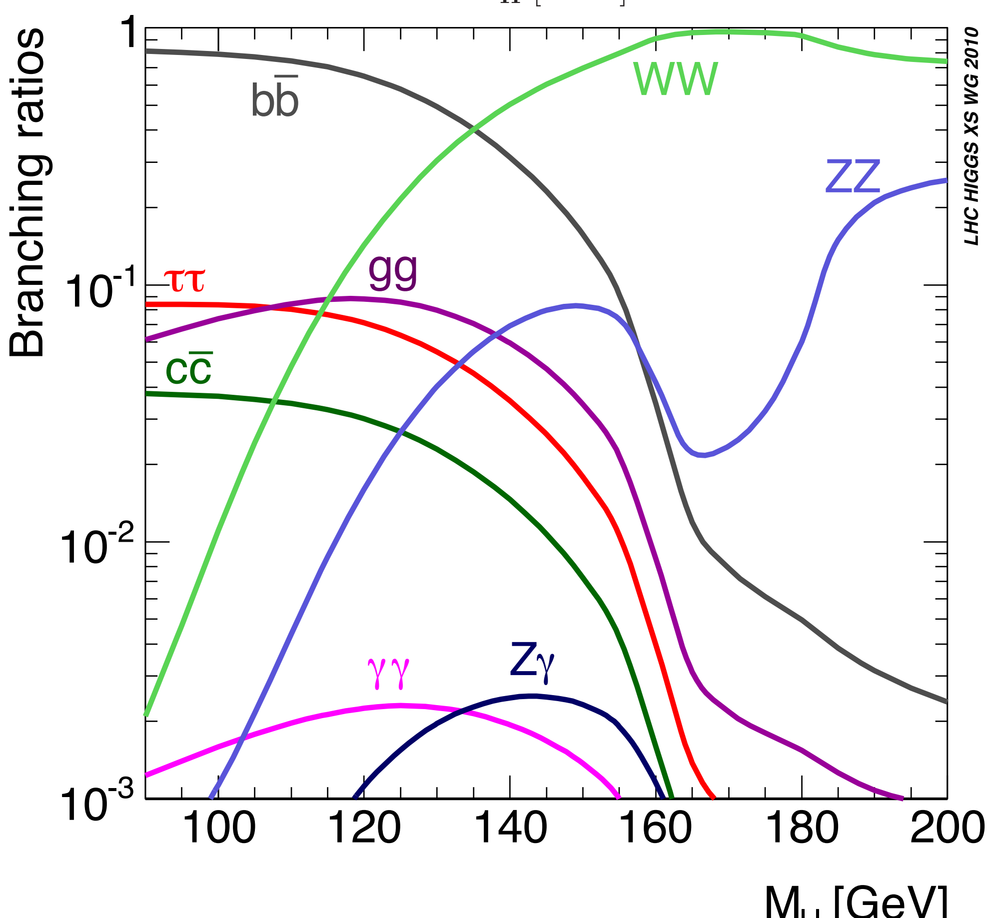




Looking into the Light Region

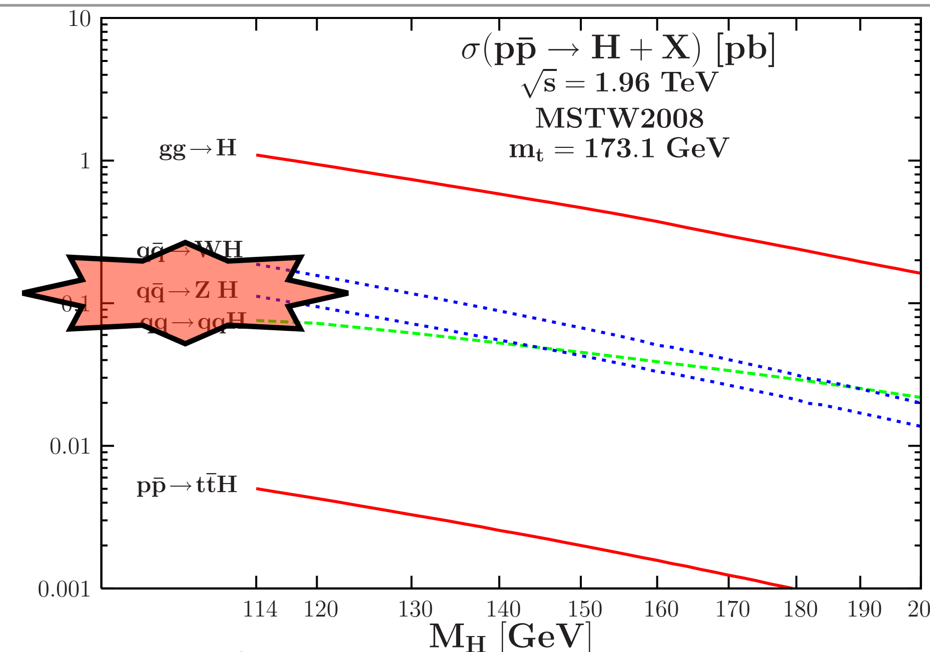
- There are multiple production and decay modes
- WH & ZH (H to bb) are dominant contributors (≲135 GeV/c²) (H to bb is dominated by background)
- These channels are analyzed individually ("optimized" analyses)

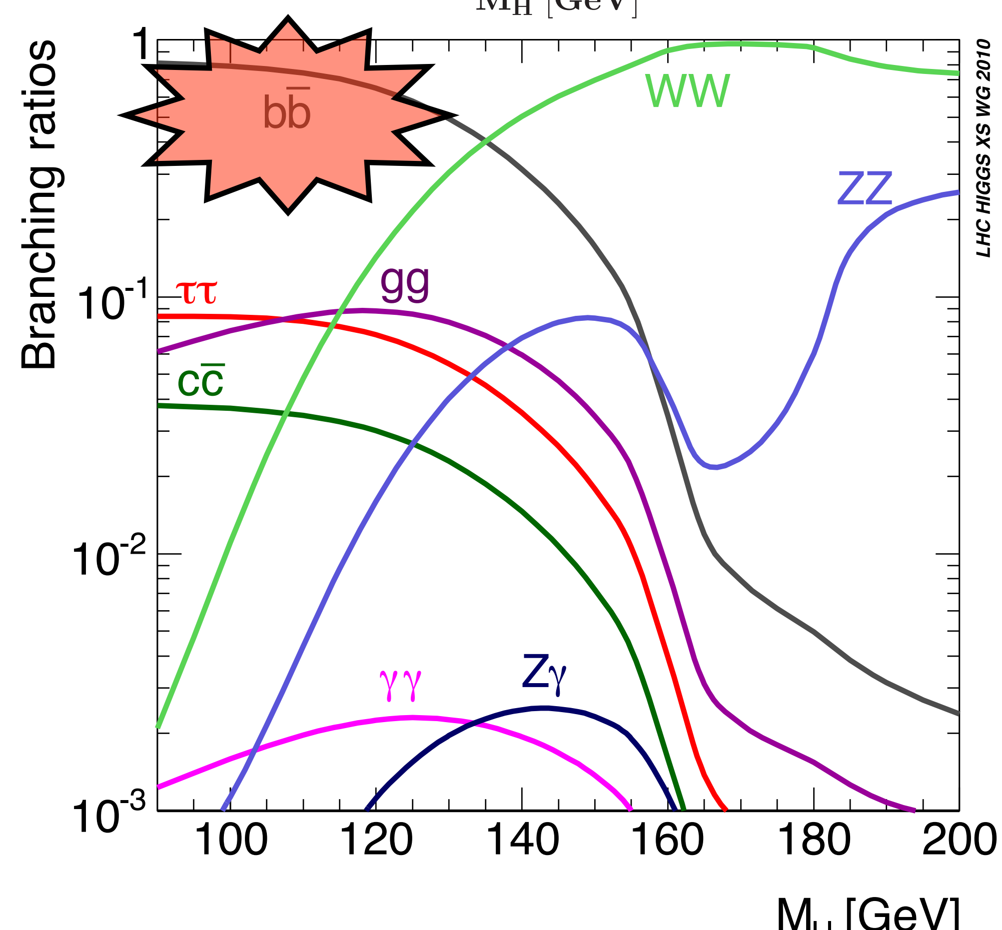


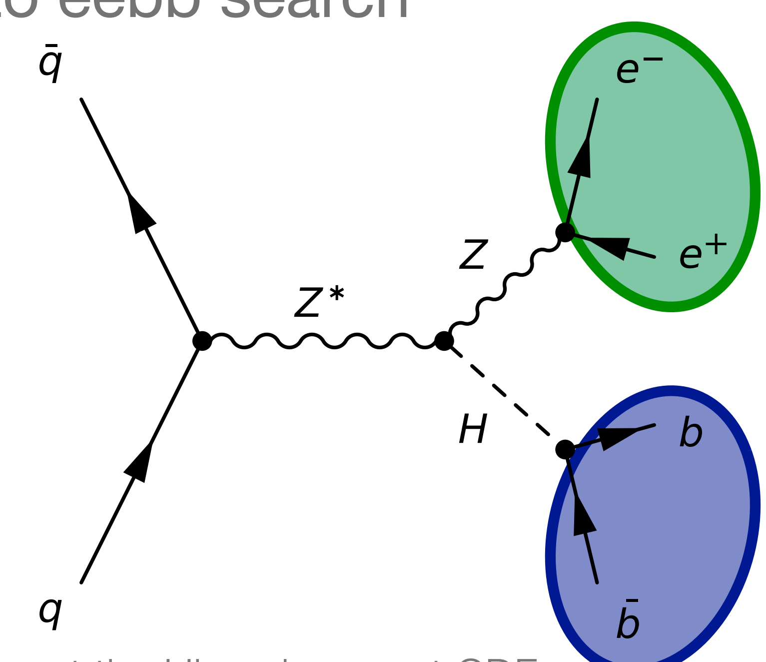


Looking into the Light Region

- There are multiple production and decay modes
- WH & ZH (H to bb) are dominant contributors (≲135 GeV/c^2) (H to bb is dominated by background)
- These channels are analyzed individually ("optimized" analyses)
- Here, I'll discuss some aspects of CDF's ZH to eebb search







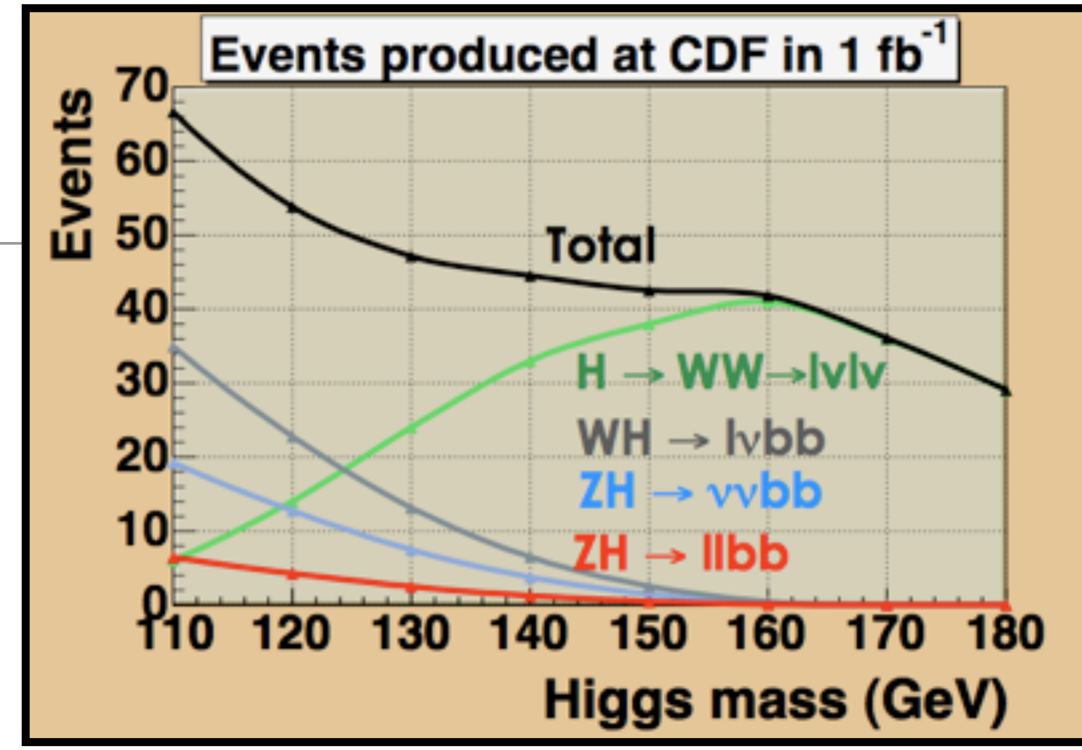
ZH to eebb Search

ZH to eebb Search

- We don’t expect many events: cut-and-count methods would require atto-barnes of data (1000 years)

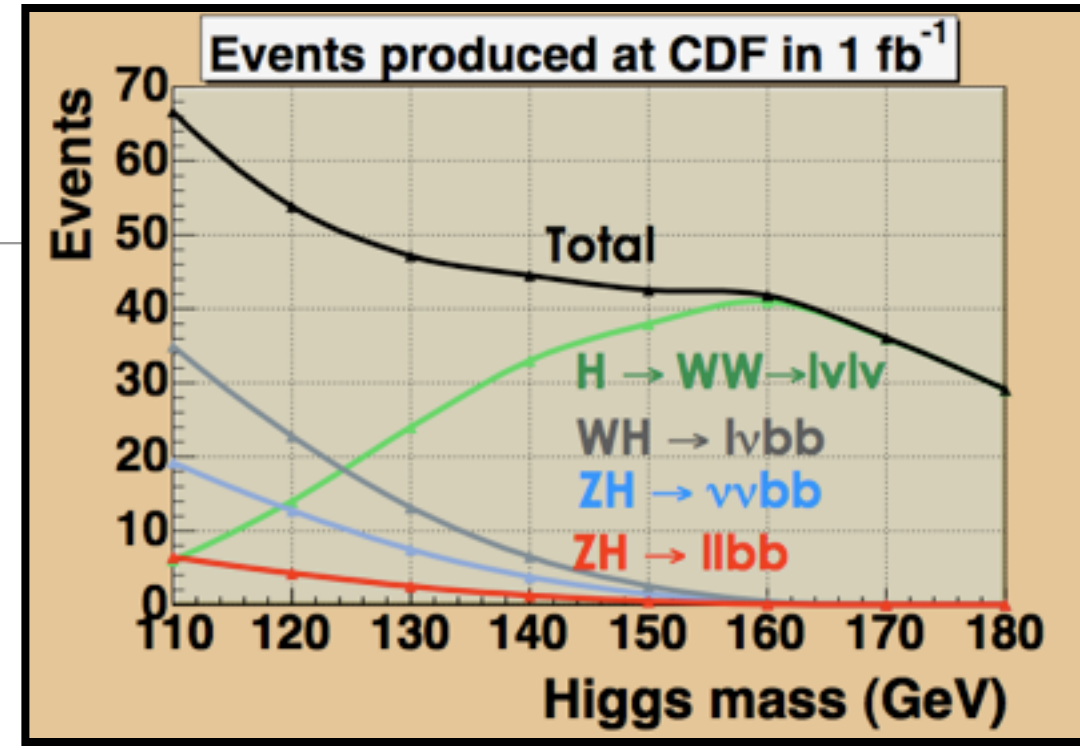
ZH to eebb Search

- We don't expect many events: cut-and-count methods would require atto-barnes of data (1000 years)



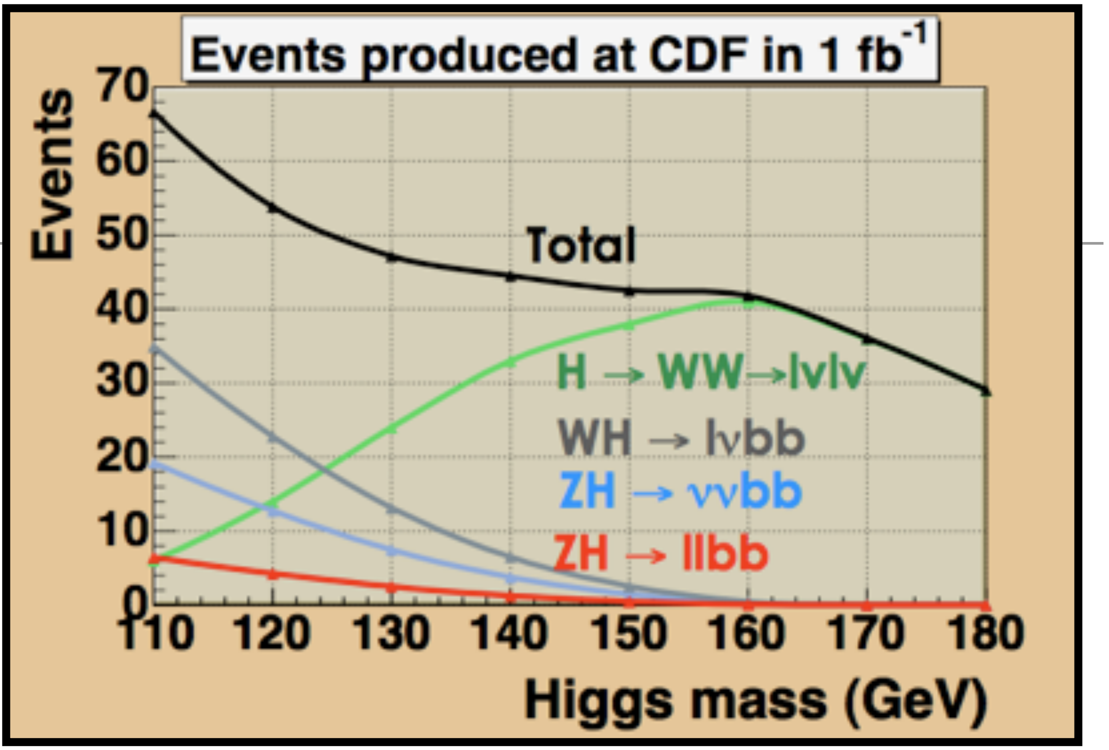
ZH to eebb Search

- We don't expect many events: cut-and-count methods would require atto-barnes of data (1000 years)
- Instead, final discriminant is a neural-network output distribution

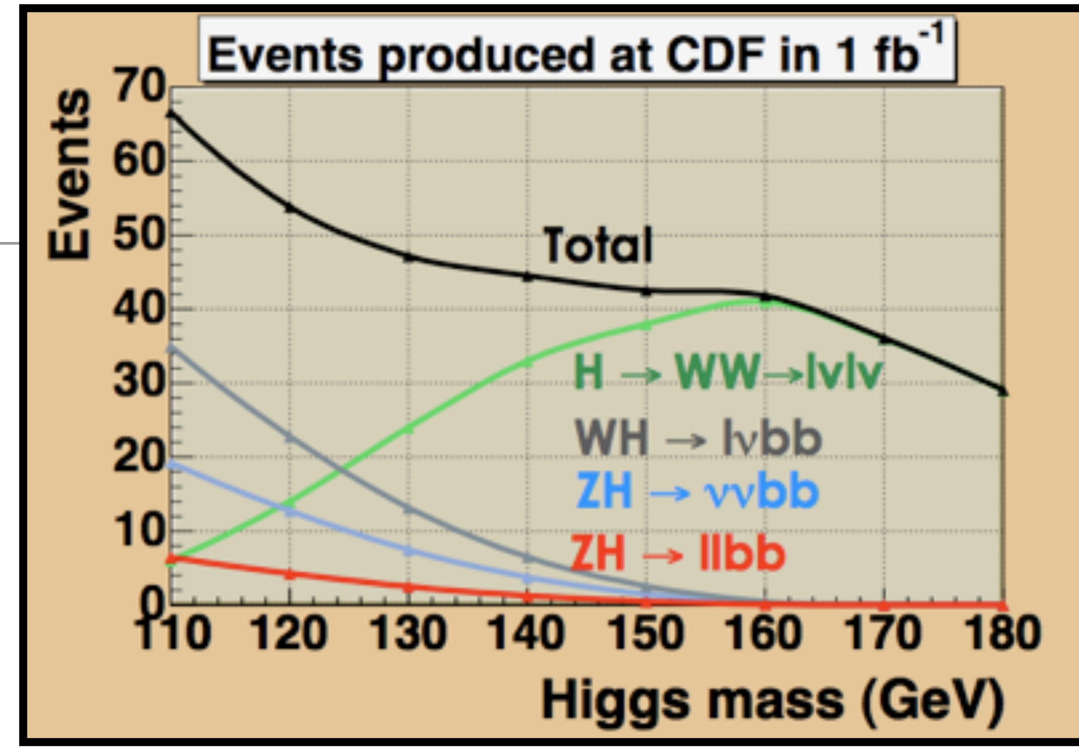


ZH to eebb Search

- We don't expect many events: cut-and-count methods would require atto-barnes of data (1000 years)
- Instead, final discriminant is a neural-network output distribution



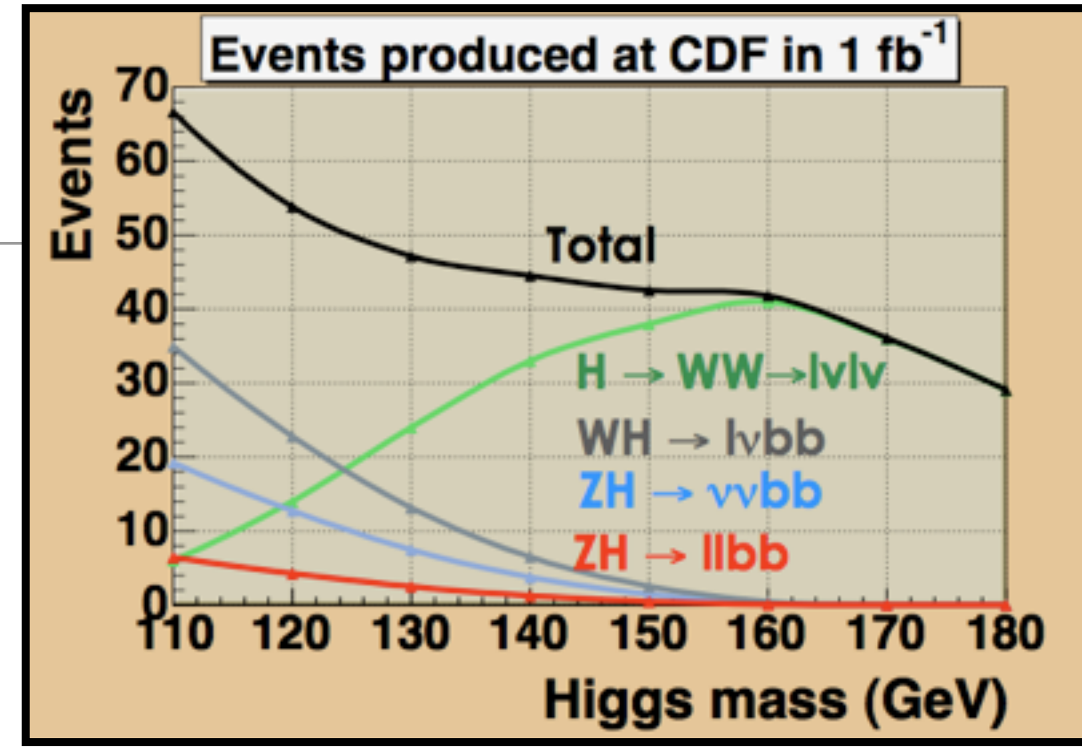
ZH to eebb Search

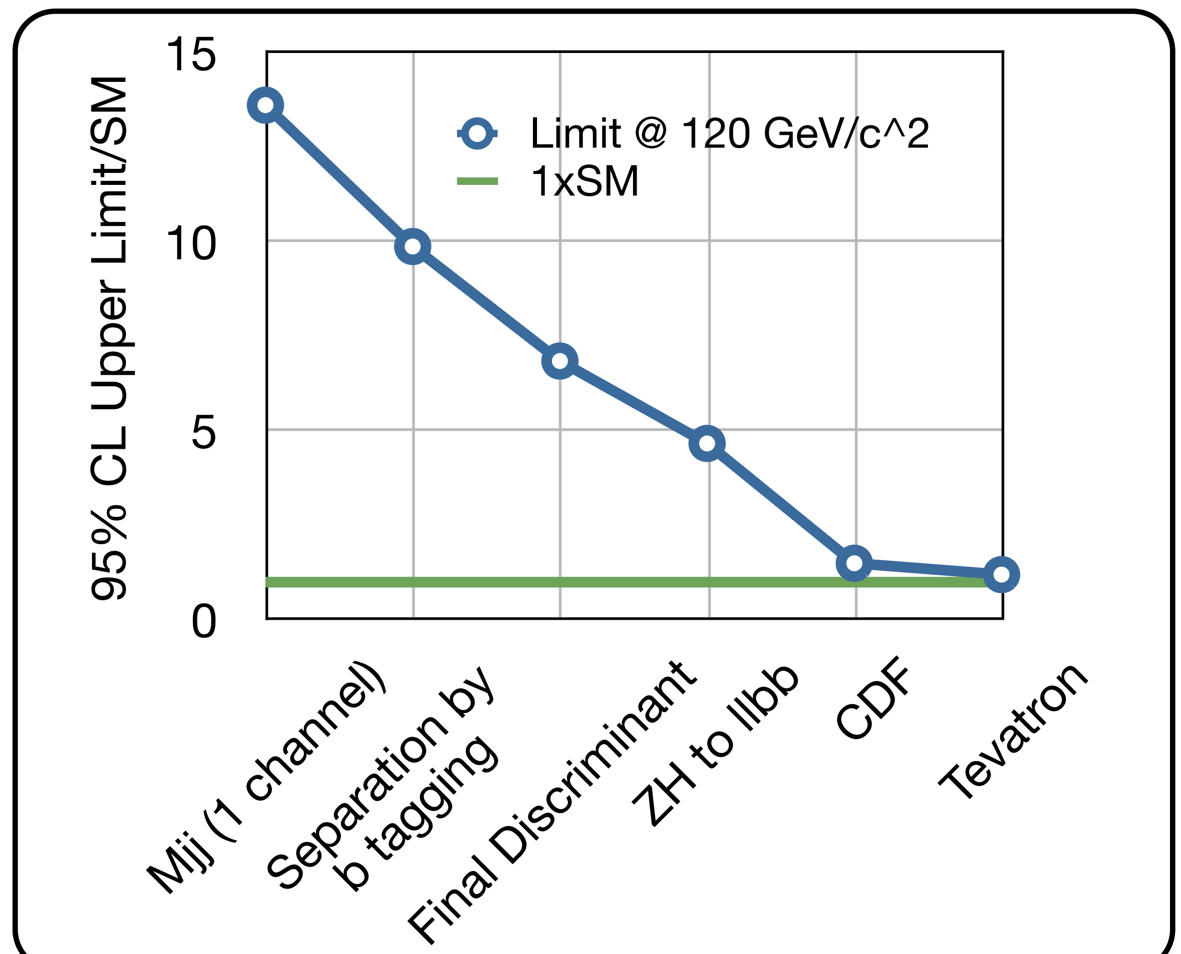


- We don't expect many events: cut-and-count methods would require atto-barnes of data (1000 years)
- Instead, final discriminant is a neural-network output distribution
- Advanced/sophisticated techniques are used to improve sensitivity:

ZH to eebb Search

- We don't expect many events: cut-and-count methods would require atto-barnes of data (1000 years)
- Instead, final discriminant is a neural-network output distribution
- Advanced/sophisticated techniques are used to improve sensitivity:

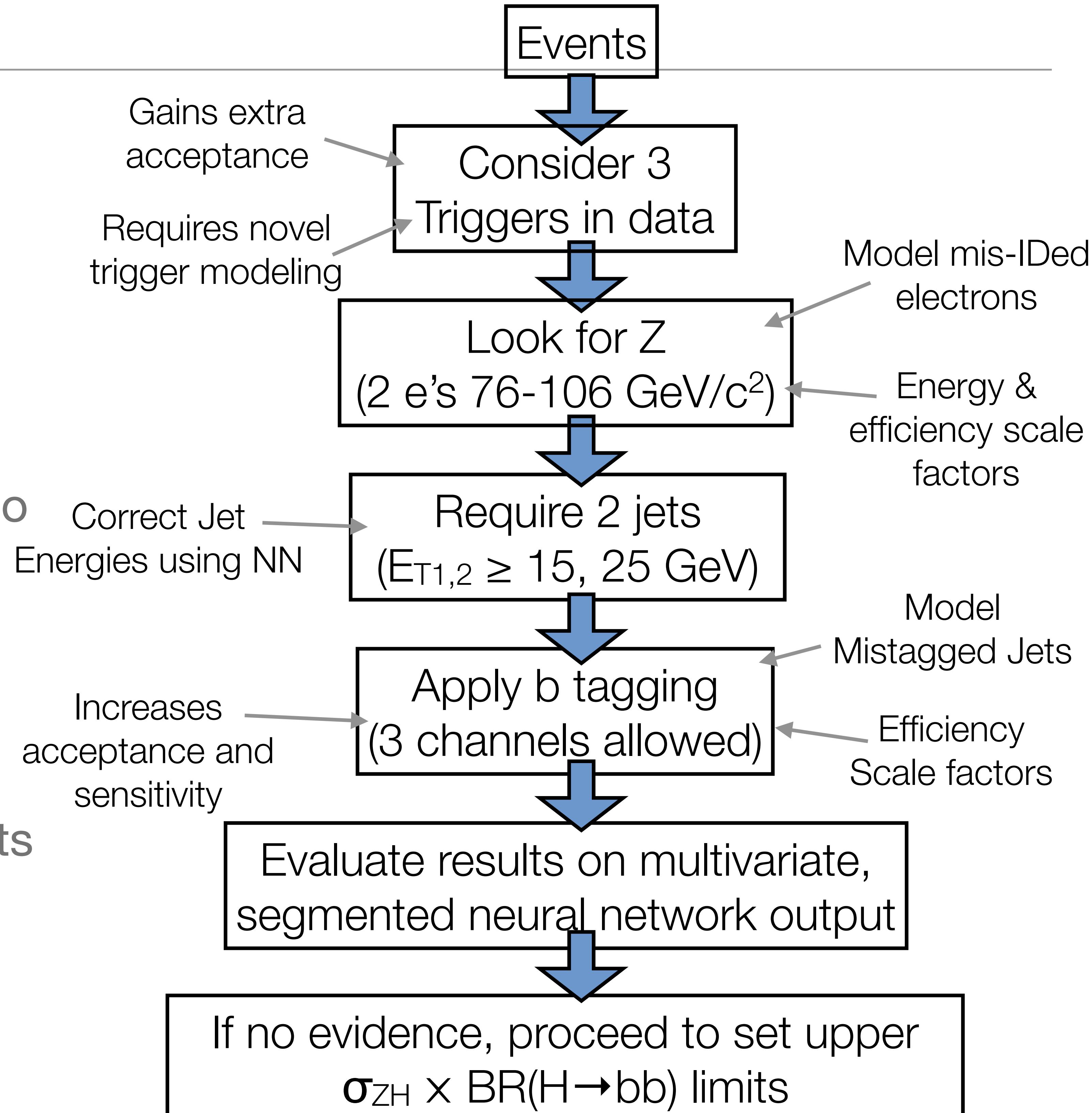




ZH to eebb Search

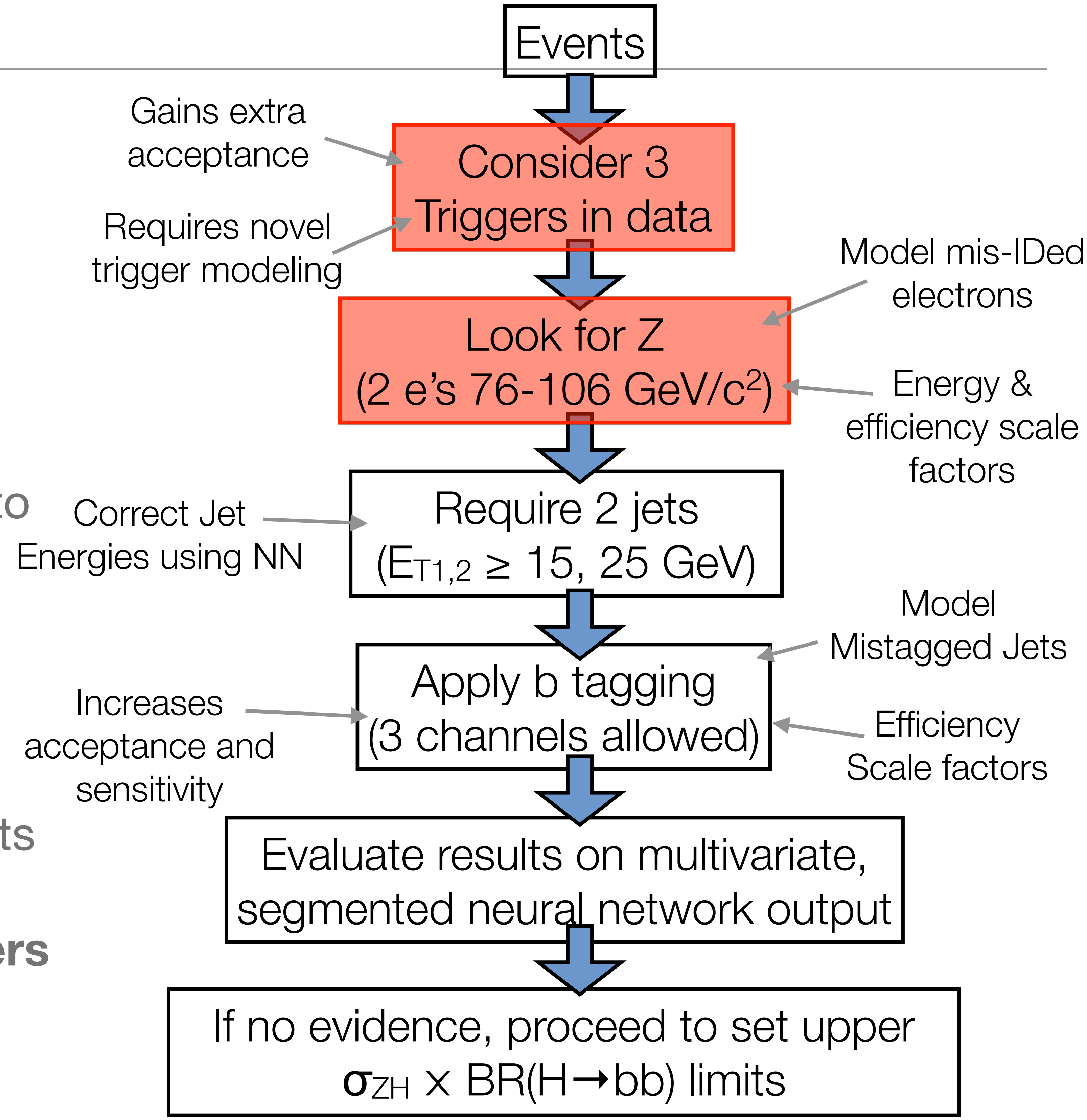
ZH to eebb Search

- Mature analysis using many sophisticated techniques with two goals:
    - increase acceptance
    - improve discriminant (due to increase in bkg from 1)
    - ➡Lots of neural networks, some boosted decision trees... to exact the most information out of the events



ZH to eebb Search

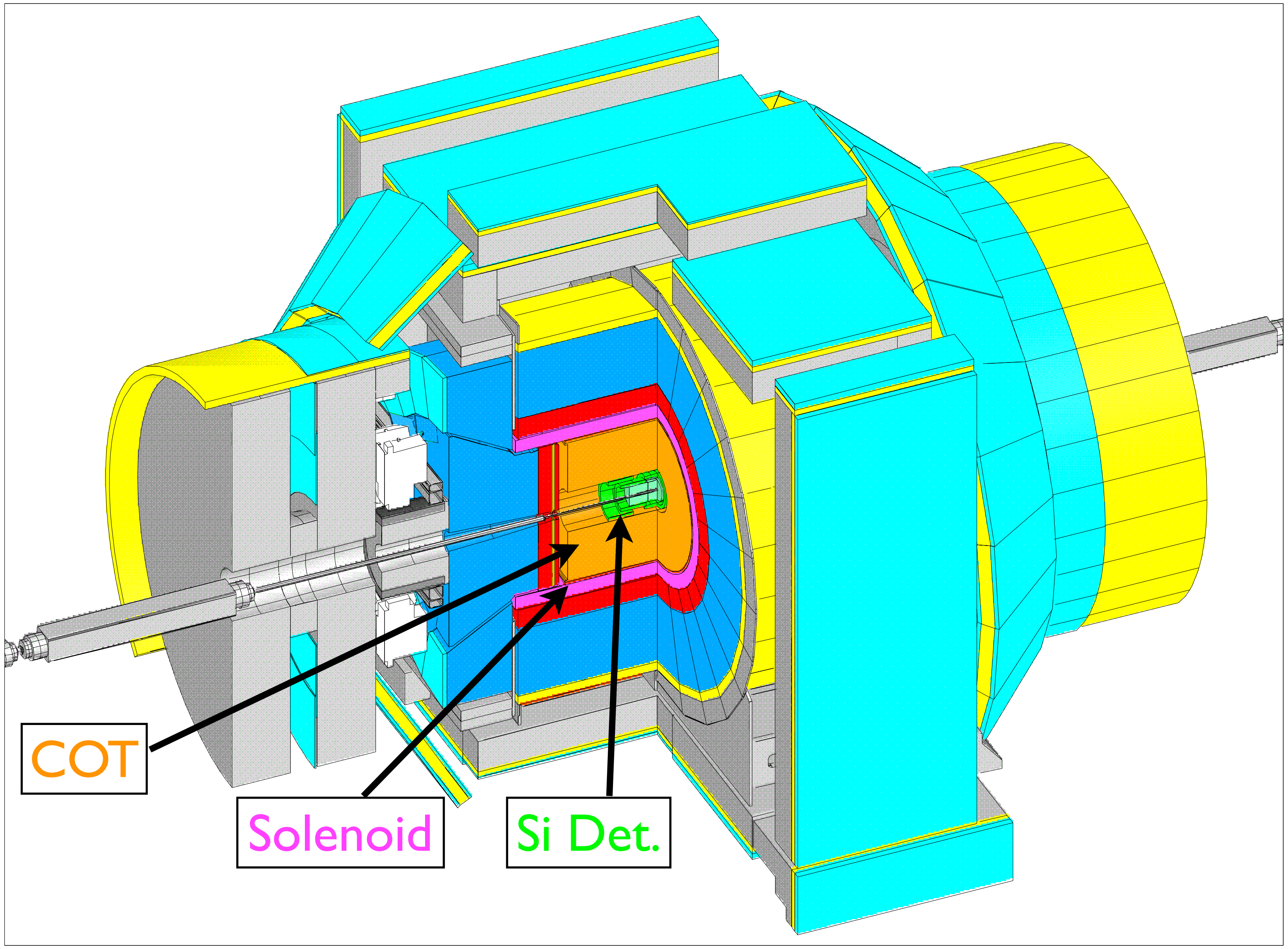
- Mature analysis using many sophisticated techniques with two goals:
  - increase acceptance
  - improve discriminant (due to increase in bkg from 1)
  - ➡Lots of neural networks, some boosted decision trees... to exact the most information out of the events
- Here, I will focus on the **triggers** and **electron ID**



What do e's look like at CDF

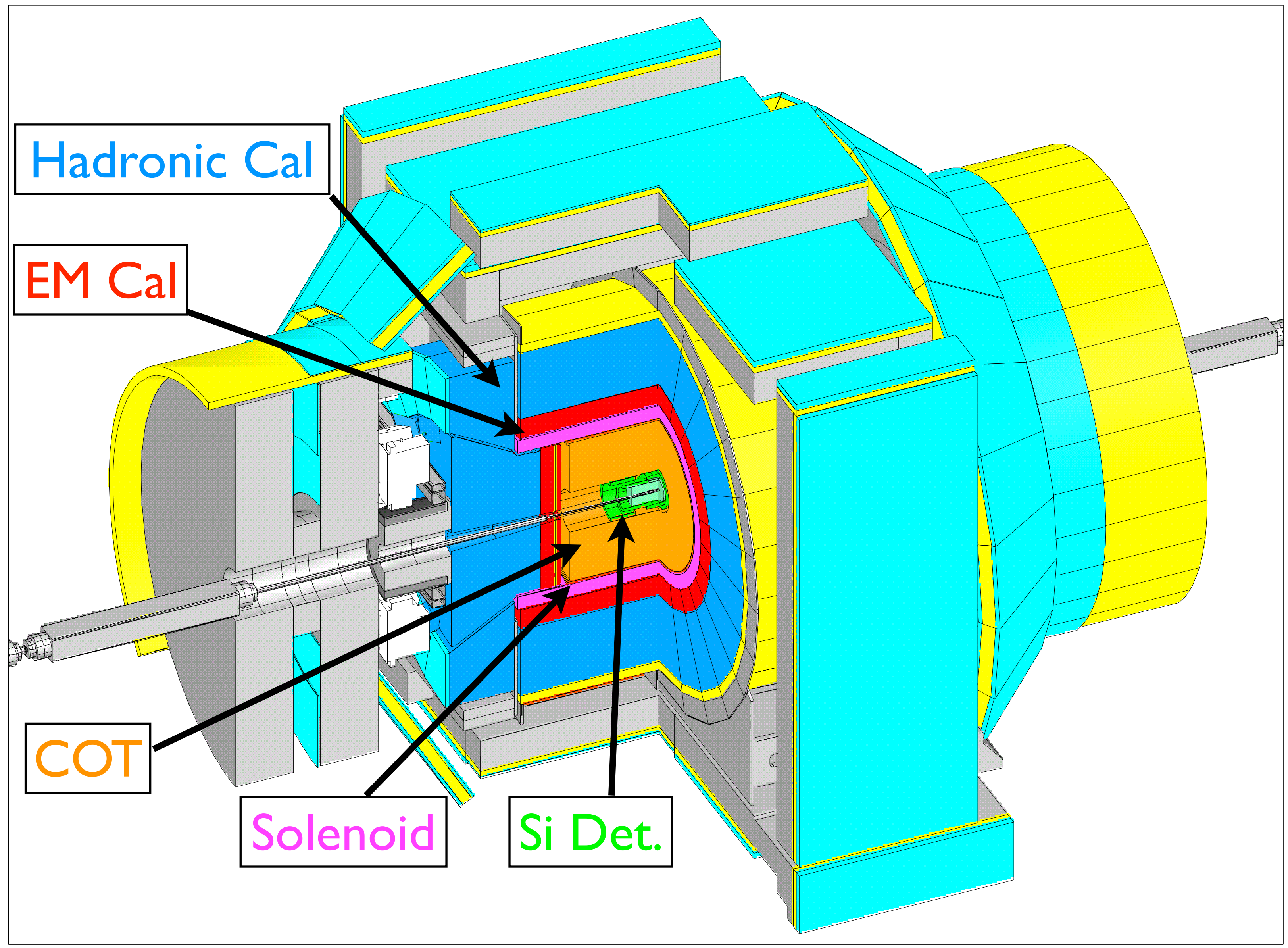
What do e’s look like at CDF

- Tracking within a solenoid (1.4 T): Silicon system surrounded by the COT (wire chamber)



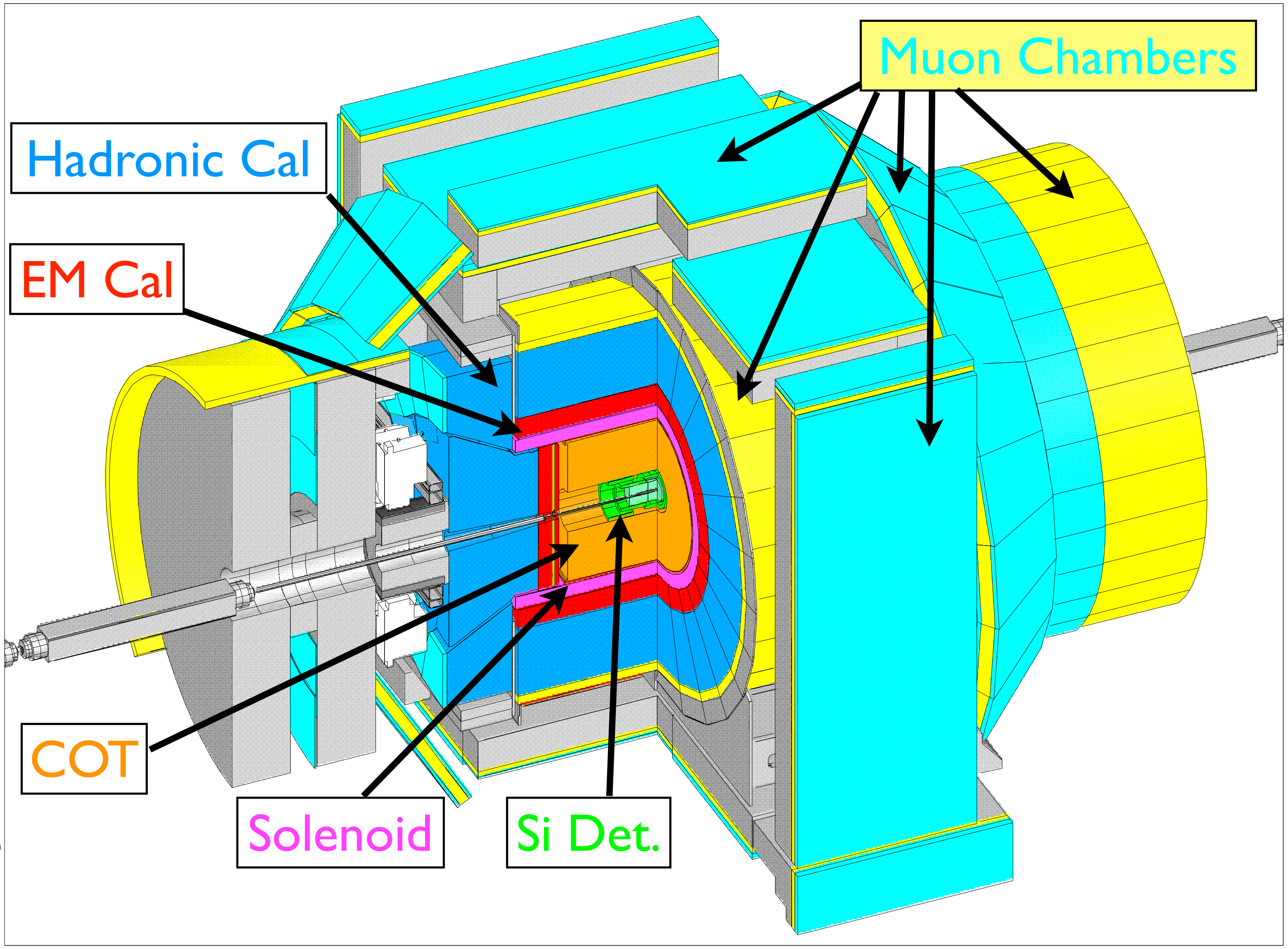
What do e's look like at CDF

- Tracking within a solenoid (1.4 T): Silicon system surrounded by the COT (wire chamber)
- Calorimetry: EM sampling calorimeter followed by Hadronic sampling calorimeter
  - EM calorimeters have "shower maximum" detectors for shape and position information

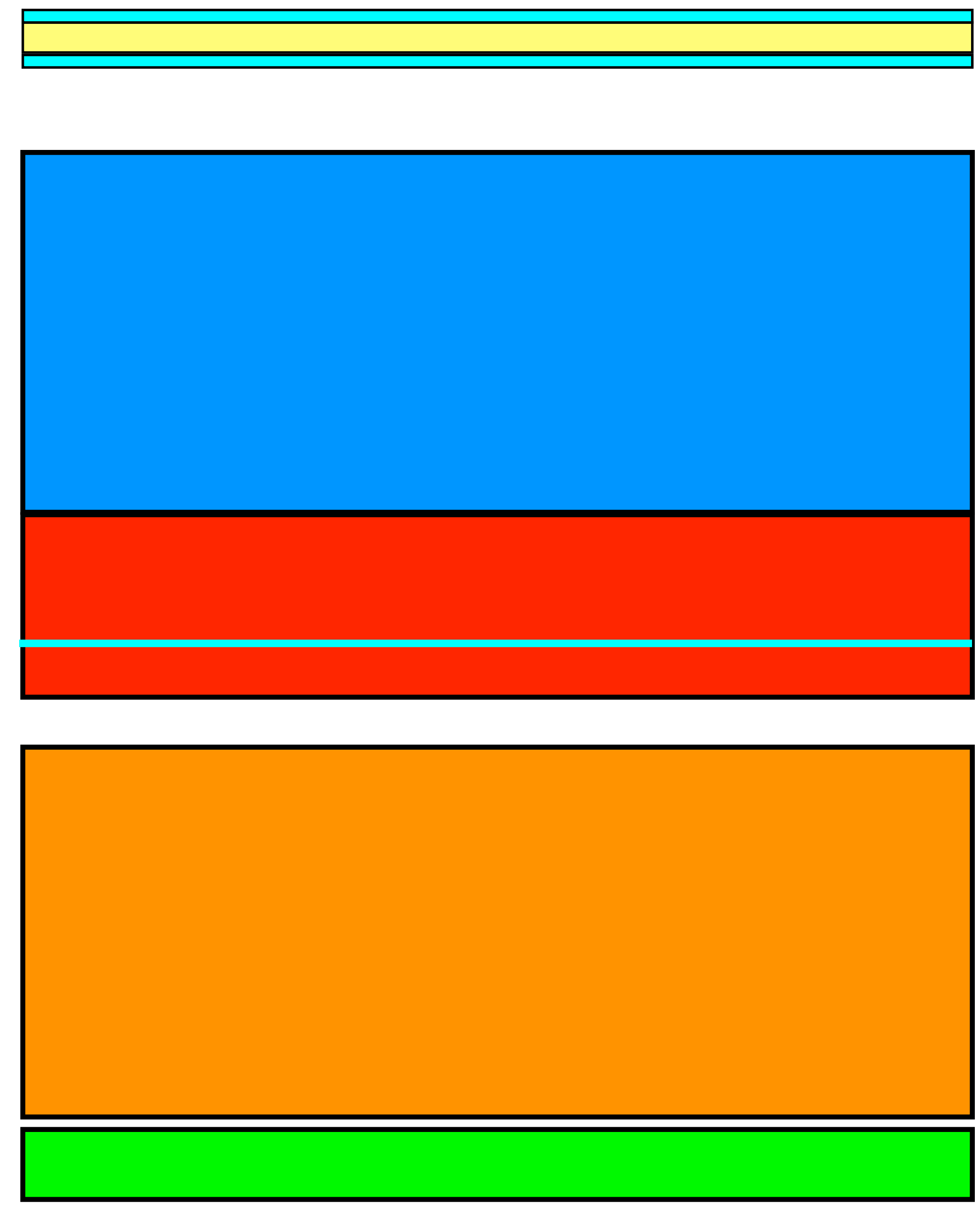


What do e's look like at CDF

- Tracking within a solenoid (1.4 T): Silicon system surrounded by the COT (wire chamber)
- Calorimetry: EM sampling calorimeter followed by Hadronic sampling calorimeter
  - EM calorimeters have "shower maximum" detectors for shape and position information
- Muon chambers are the outer-most detectors

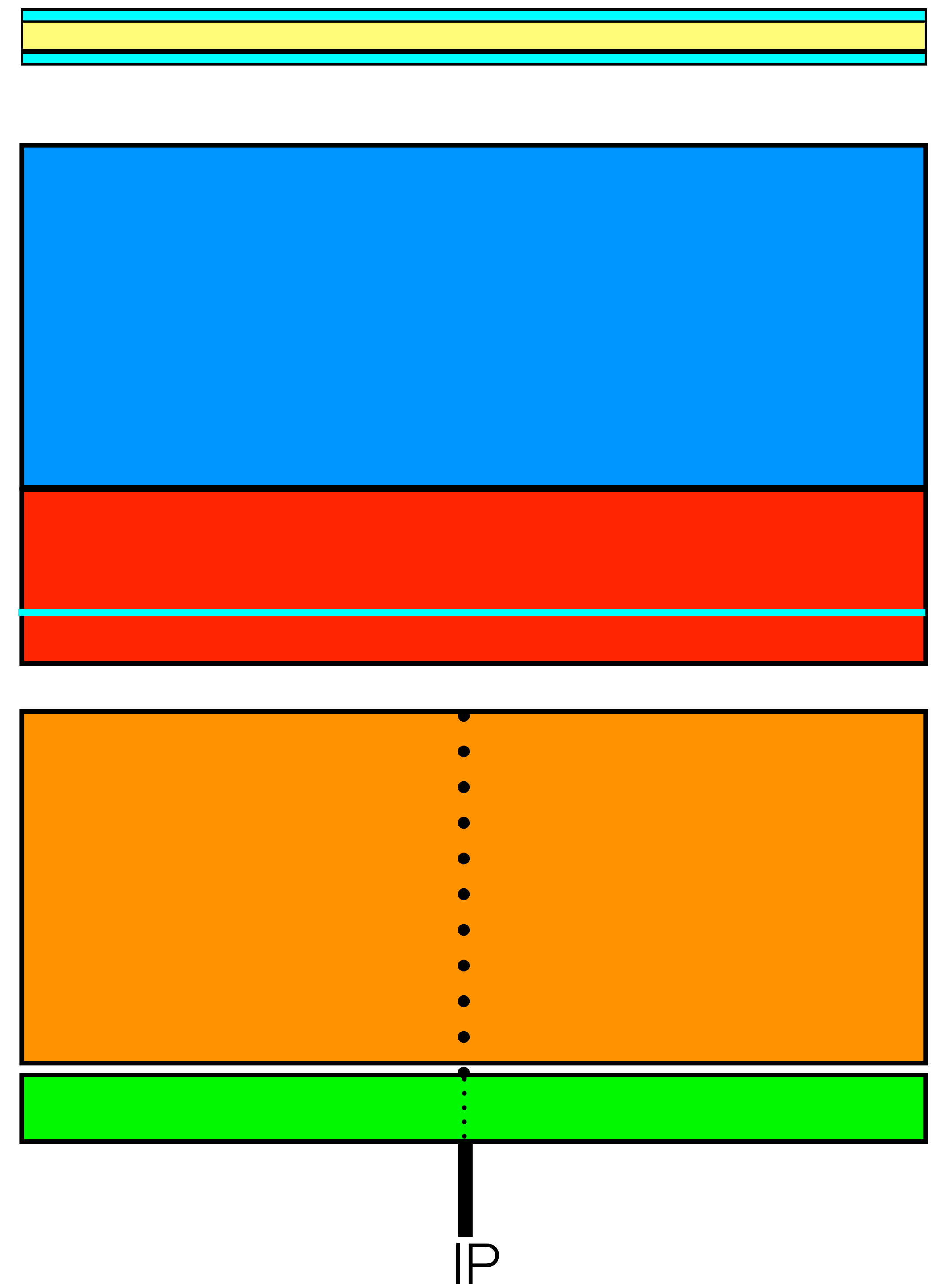


What do electrons look like at CDF? (central, $|\eta|<1.1$)



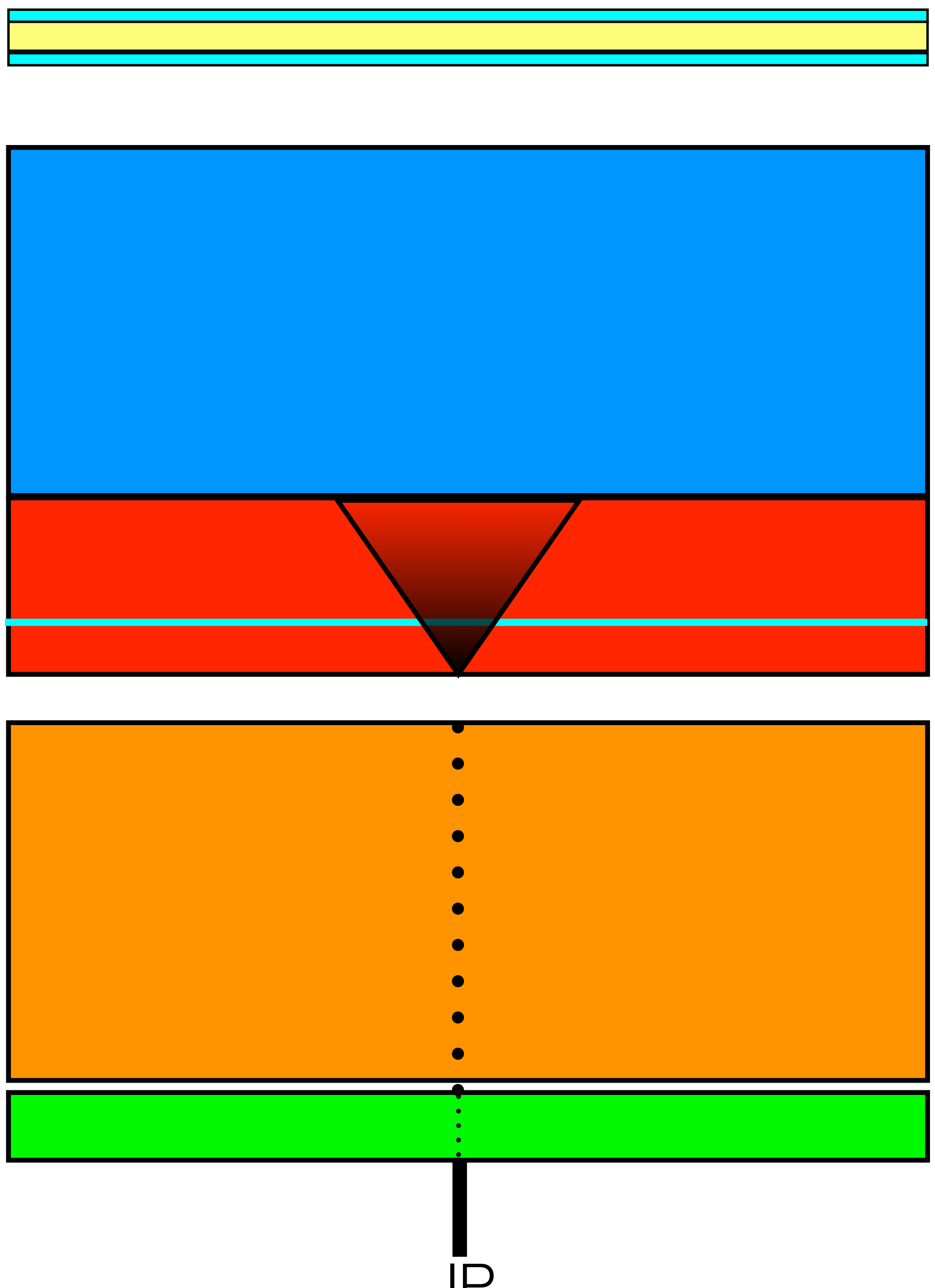
What do electrons look like at CDF? (central, $|\eta|<1.1$)

- Track in Silicon system, Track in COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation



What do electrons look like at CDF? (central, $|\eta|<1.1$)

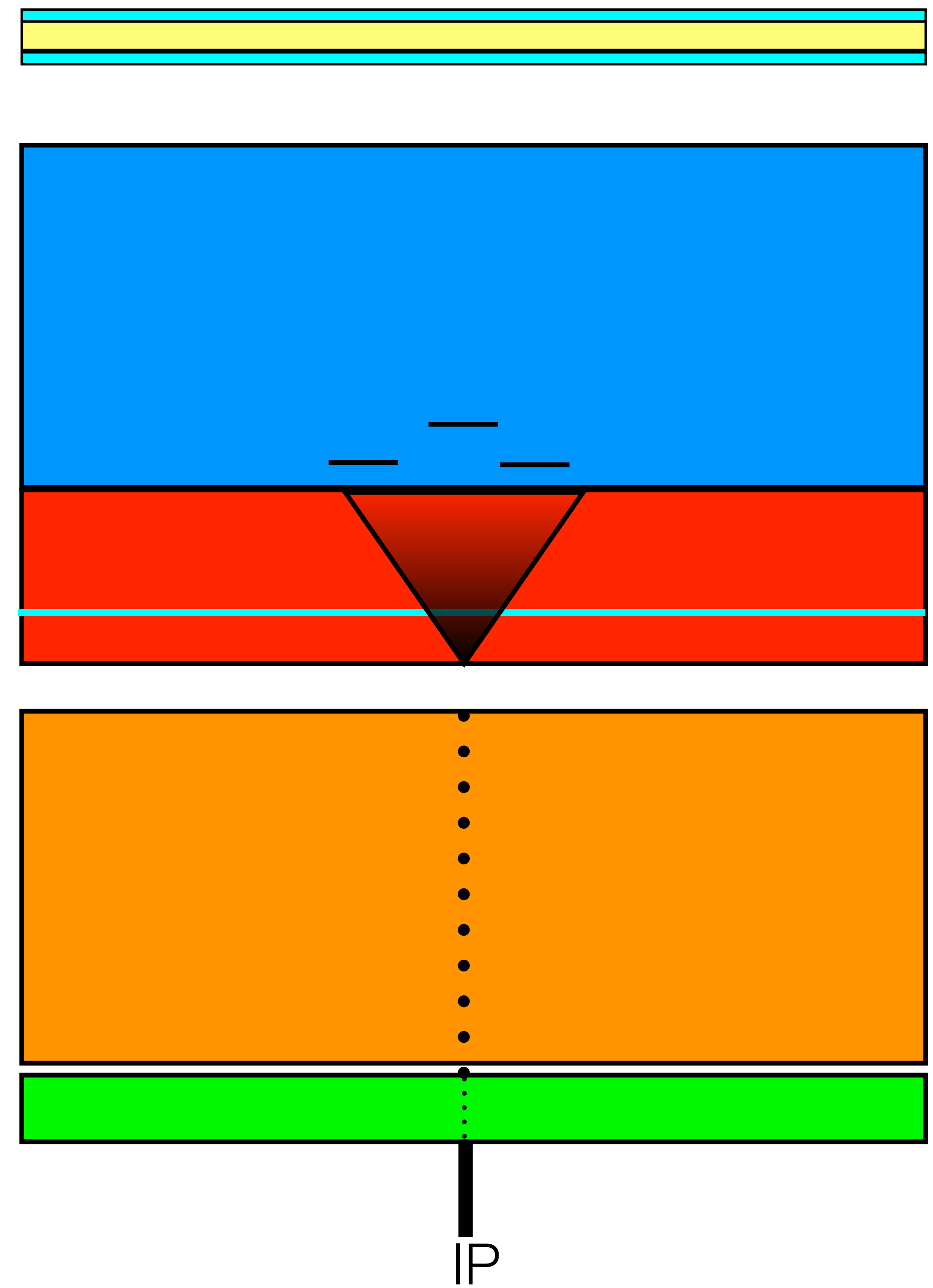
- Track in Silicon system, Track in COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation
- Most of the energy deposited in the EM calorimeter. Shower shape information from "shower max" detector



isolation ratio: (E(cluster) - E(el))/E(cluster)

What do electrons look like at CDF? (central, $|\eta|<1.1$)

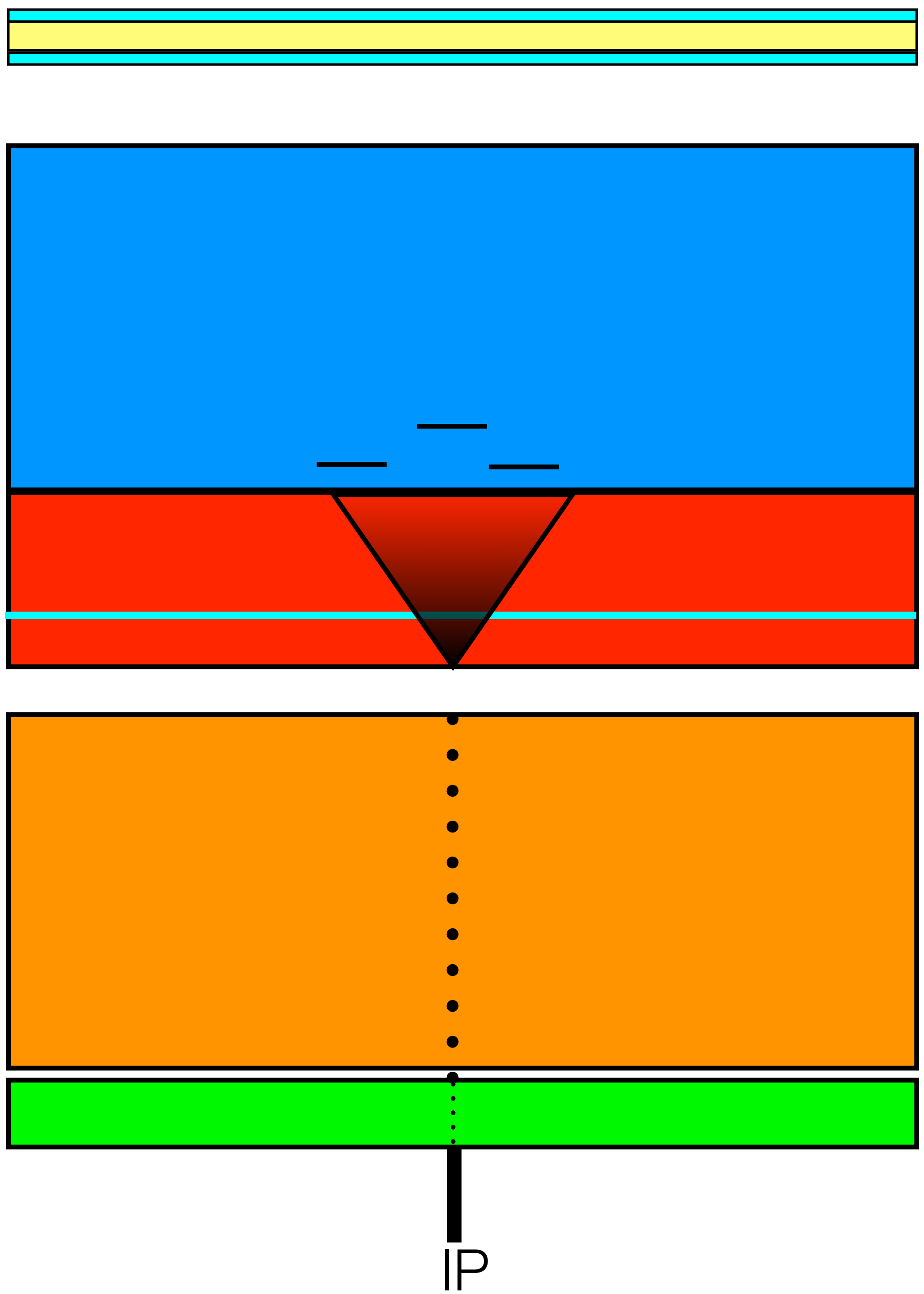
- Track in Silicon system, Track in COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation
- Most of the energy deposited in the EM calorimeter. Shower shape information from "shower max" detector
- Comparatively low energy deposited in Hadronic Calorimeter
  - L_{shr}, Em. Energy, Had. Energy, Had./Em, E/P, isolation ratio, total (R=0.4) cal. isolation



isolation ratio: (E(cluster) - E(el))/E(cluster)

What do electrons look like at CDF? (central, $|\eta|<1.1$)

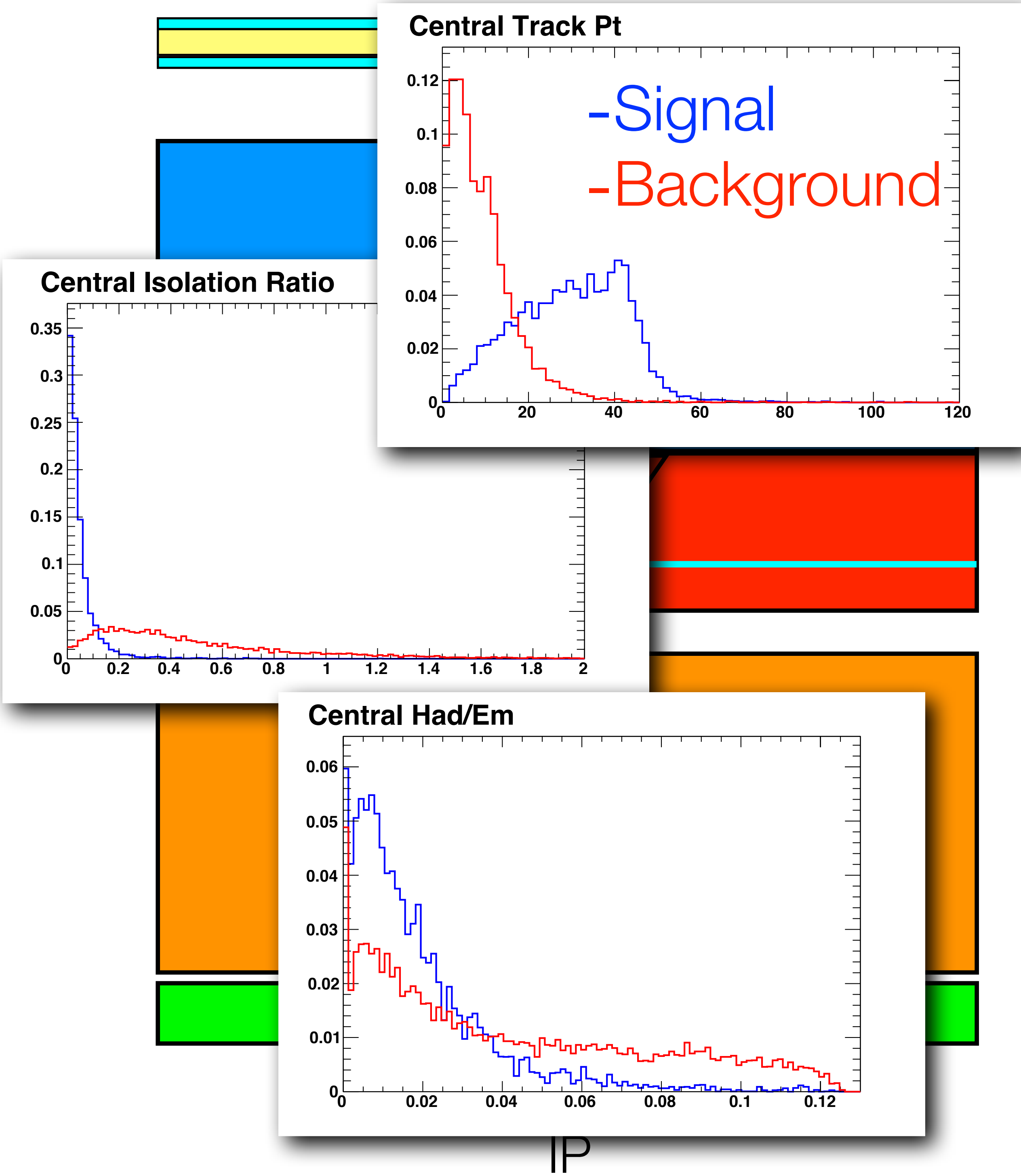
- Track in Silicon system, Track in COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation
- Most of the energy deposited in the EM calorimeter. Shower shape information from "shower max" detector
- Comparatively low energy deposited in Hadronic Calorimeter
  - L_{shr}, Em. Energy, Had. Energy, Had./Em, E/P, isolation ratio, total (R=0.4) cal. isolation
- Quiet muon chambers



isolation ratio: (E(cluster) - E(el))/E(cluster)

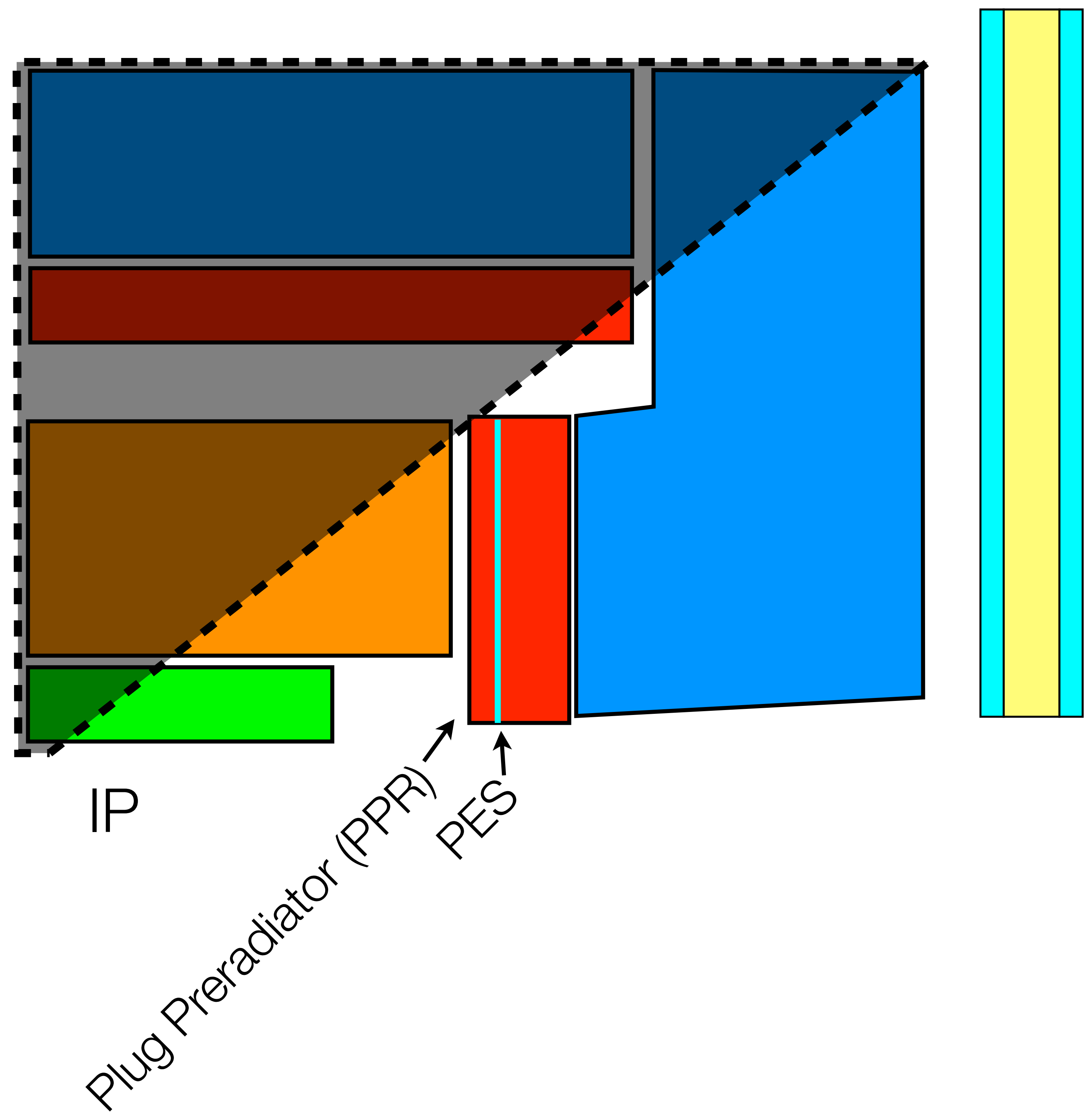
What do electrons look like at CDF? (central, $|\eta|<1.1$)

- Track in Silicon system, Track in COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation
- Most of the energy deposited in the EM calorimeter. Shower shape information from "shower max" detector
- Comparatively low energy deposited in Hadronic Calorimeter
  - L_{shr}, Em. Energy, Had. Energy, Had./Em, E/P, isolation ratio, total (R=0.4) cal. isolation
- Quiet muon chambers
- Signal=electrons
  Background = mostly jets, possibly taus or photons (fake electrons)



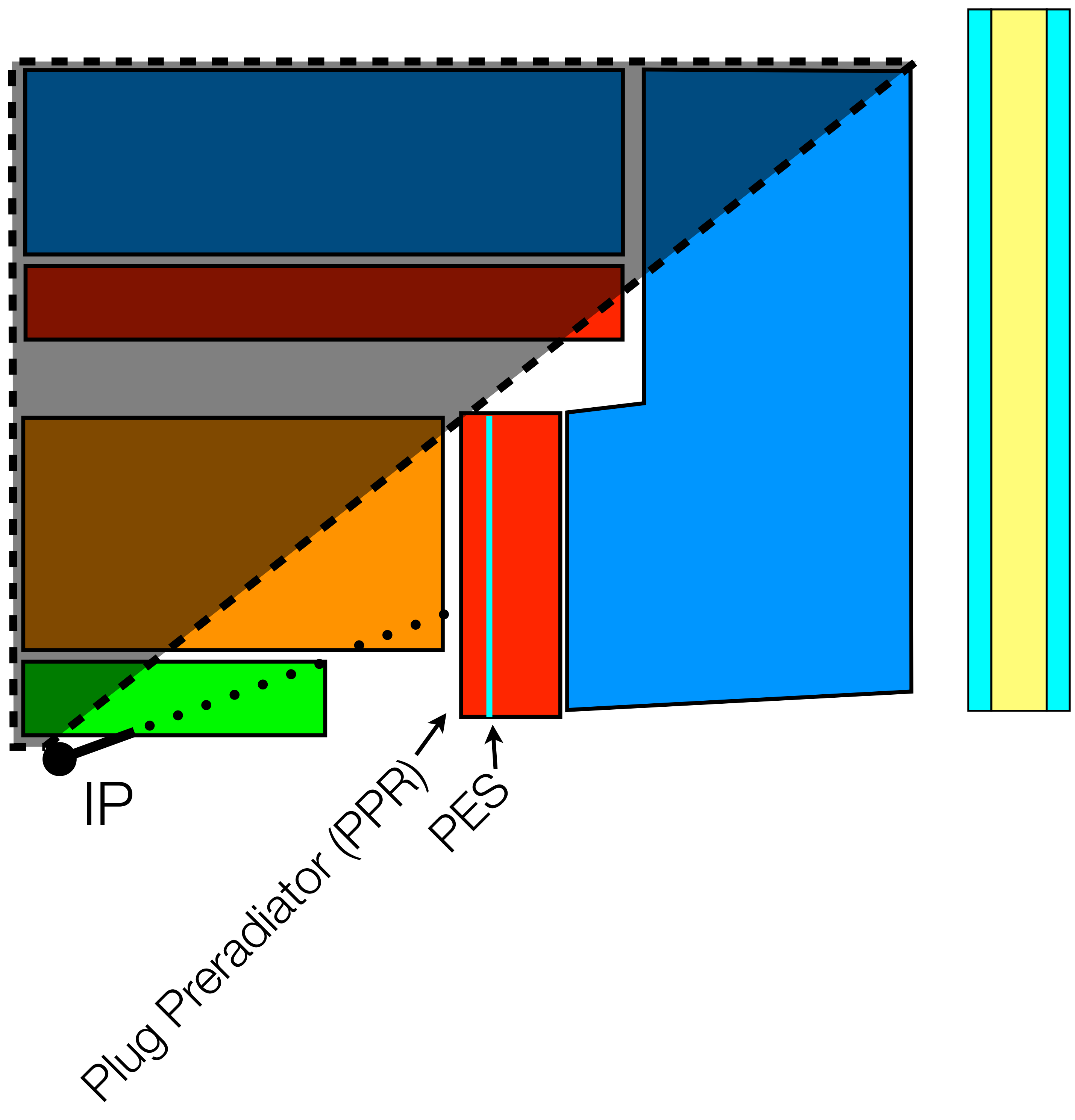
isolation ratio: (E(cluster) - E(el))/E(cluster)

What do electrons look like at CDF? (forward, $1.1<|\eta|\lesssim 3.6$)



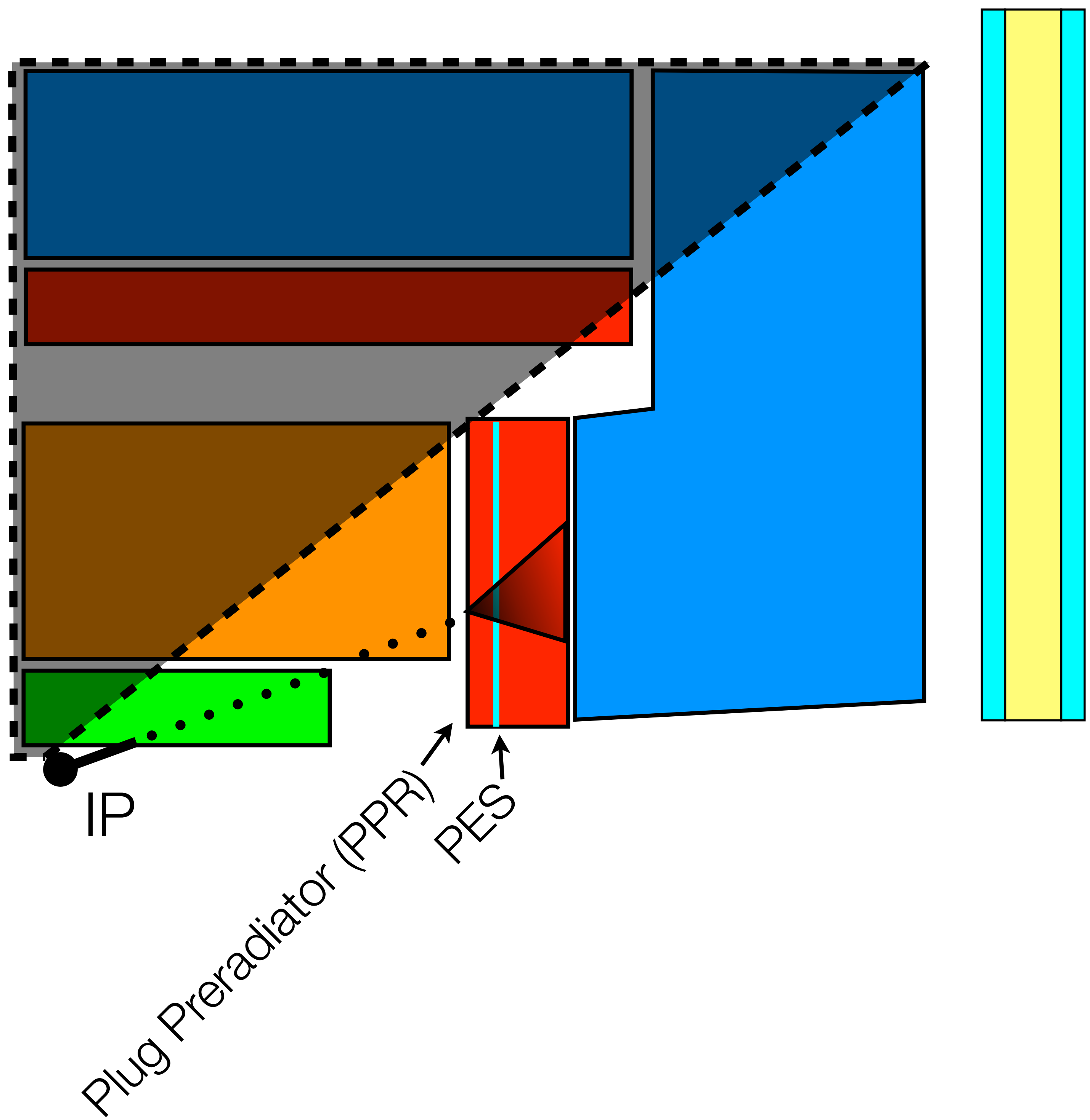
What do electrons look like at CDF? (forward, $1.1<|\eta|\lesssim 3.6$)

- Some/few hits in Silicon system and COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation



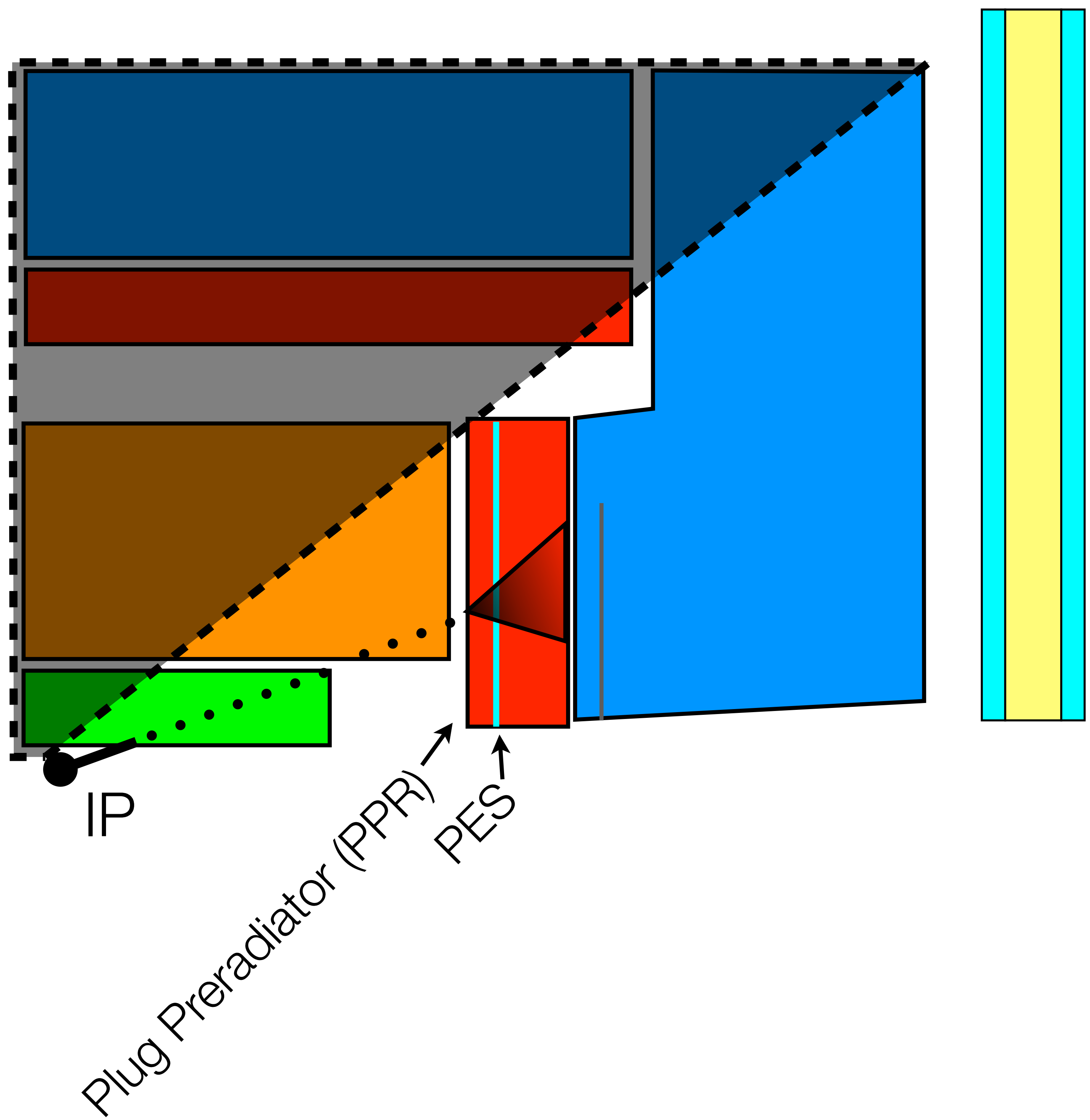
What do electrons look like at CDF? (forward, $1.1<|\eta|\lesssim 3.6$)

- Some/few hits in Silicon system and COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation
- Most of the energy deposited in the EM calorimeter (PEM). Shower shape information from "shower max" detector (PES)



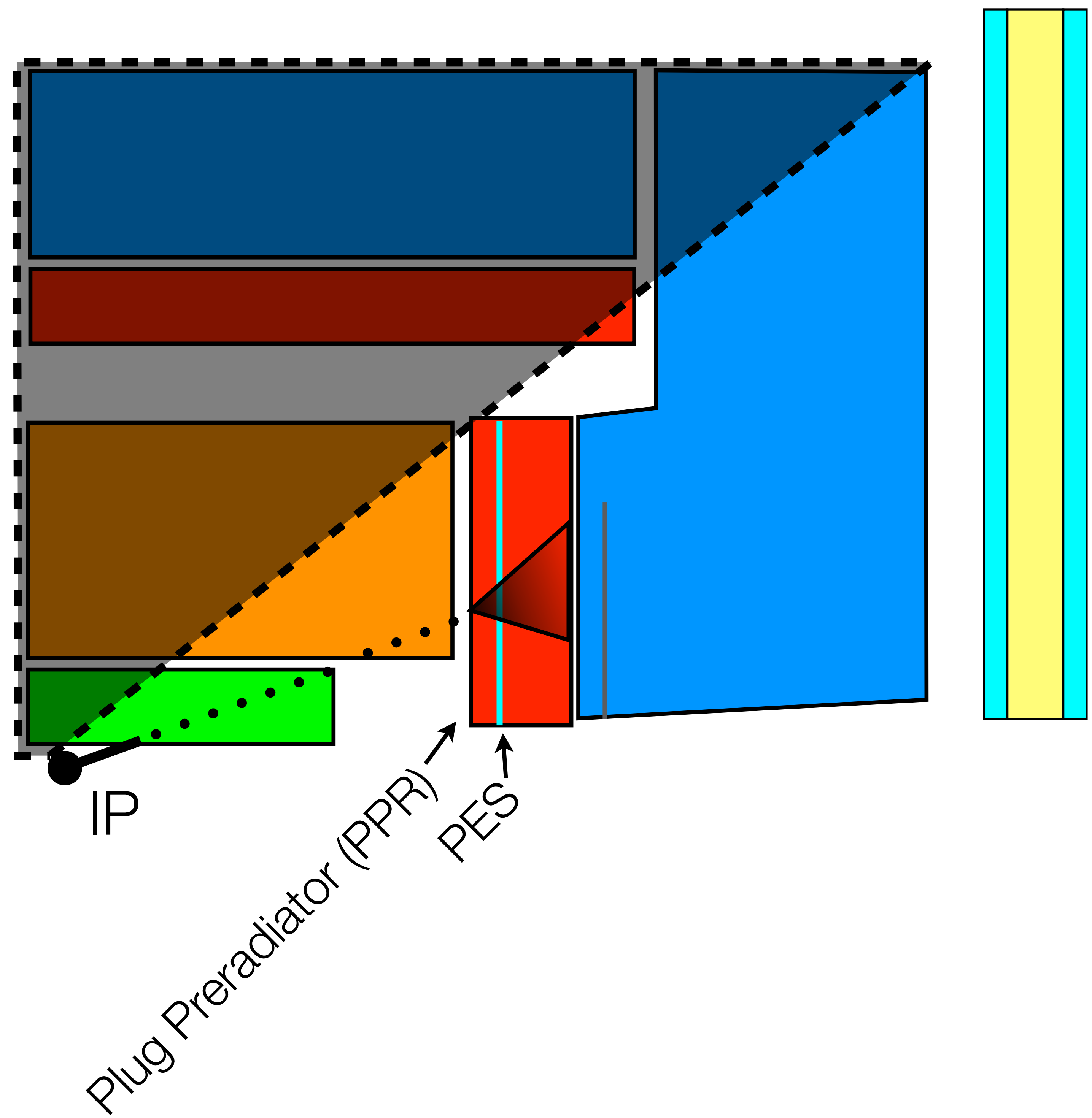
What do electrons look like at CDF? (forward, $1.1<|\eta|\lesssim 3.6$)

- Some/few hits in Silicon system and COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation
- Most of the energy deposited in the EM calorimeter (PEM). Shower shape information from "shower max" detector (PES)
- Low energy deposited in Had. Cal.
  - Em. Energy, Had. Energy, Had./Em, E/P, isolation
  - PES PEM ΔR, PES 5x9 U (V), PES energy, PEM 3x3 χ^2, PPR Energy



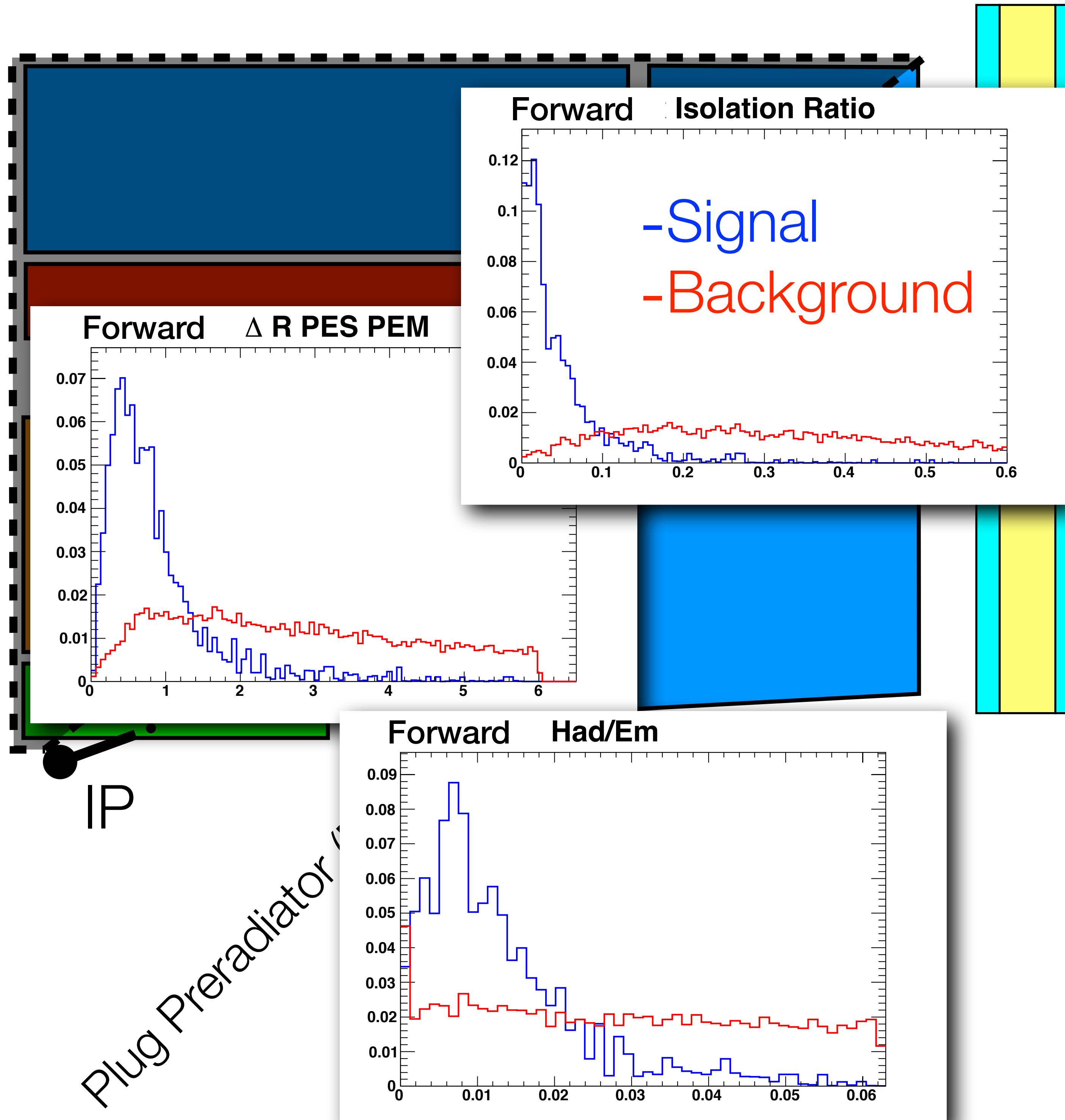
What do electrons look like at CDF? (forward, 1.1<|η|≲3.6)

- Some/few hits in Silicon system and COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation
- Most of the energy deposited in the EM calorimeter (PEM). Shower shape information from "shower max" detector (PES)
- Low energy deposited in Had. Cal.
  - Em. Energy, Had. Energy, Had./Em, E/P, isolation
  - PES PEM ΔR, PES 5x9 U (V), PES energy, PEM 3x3 χ^2, PPR Energy
- Quiet muon chambers



What do electrons look like at CDF? (forward, 1.1<|η|≲3.6)

- Some/few hits in Silicon system and COT
  - Silicon hits, # of COT hits, Track χ^2 fit, p_T, track isolation
- Most of the energy deposited in the EM calorimeter (PEM). Shower shape information from "shower max" detector (PES)
- Low energy deposited in Had. Cal.
  - Em. Energy, Had. Energy, Had./Em, E/P, isolation
  - PES PEM ΔR, PES 5x9 U (V), PES energy, PEM 3x3 χ^2, PPR Energy
- Quiet muon chambers



Goal: Improve ZH Acceptance!

Goal: Improve ZH Acceptance!

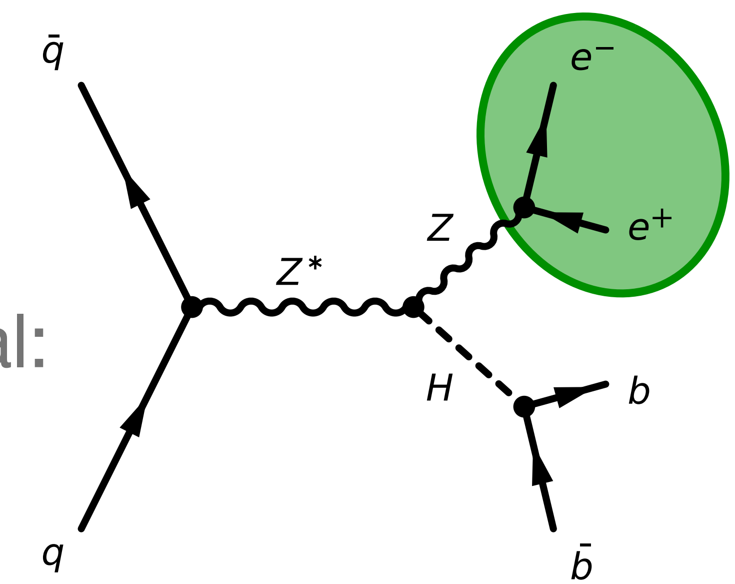
- Ideas?

Goal: Improve ZH Acceptance!

- Ideas?
- Include additional data trigger streams
  - Naturally leads to more data
  - Likely leads to more signal, but we must model the trigger performance well

Goal: Improve ZH Acceptance!

- Ideas?
- Include additional data trigger streams
  - Naturally leads to more data
  - Likely leads to more signal, but we must model the trigger performance well
- Improve electron ID efficiency!
  - More efficient electron or Z ID leads to more signal:



Goal: Improve ZH Acceptance!

- Ideas?
- Include additional data trigger streams
  - Naturally leads to more data
  - Likely leads to more signal, but we must model the trigger performance well
- Improve electron ID efficiency!
  - More efficient electron or Z ID leads to more signal:
  - Limit electron background (misidentified electrons -- "fakes")

Triggers!

Triggers!

- Tevatron produces collisions at a rate upward of 1.7 MHz

Triggers!

- Tevatron produces collisions at a rate upward of 1.7 MHz

- However, computing capacity only allowed us to store events at a rate of ~100 Hz

Triggers!

- Tevatron produces collisions at a rate upward of 1.7 MHz

- However, computing capacity only allowed us to store events at a rate of ~100 Hz

- Solution: Triggers!
    - A trigger applies a set of requirements on data events in an attempt to save only interesting events (example:)

- This analysis considered events saved due to their electron-like qualities

Triggers!

- Tevatron produces collisions at a rate upward of 1.7 MHz

- However, computing capacity only allowed us to store events at a rate of ~100 Hz

- Solution: Triggers!
  - A trigger applies a set of requirements on data events in an attempt to save only interesting events (example:)

Trigger Name	Level 1	Level 2	Level 3
Z NOTRACK	$E_T \geq 18$ Gev Central Had/Em ≤ 0.125 Plug Had/Em ≤ 0.0625 two objects	cluster $\lvert\eta\rvert < 3.6$ cluster $E_T \geq 16$ Gev cluster Had/Em ≤ 0.125 two clusters	two objects $E_T \geq 18$ GeV

- This analysis considered events saved due to their electron-like qualities

Trigger Model

Trigger Model

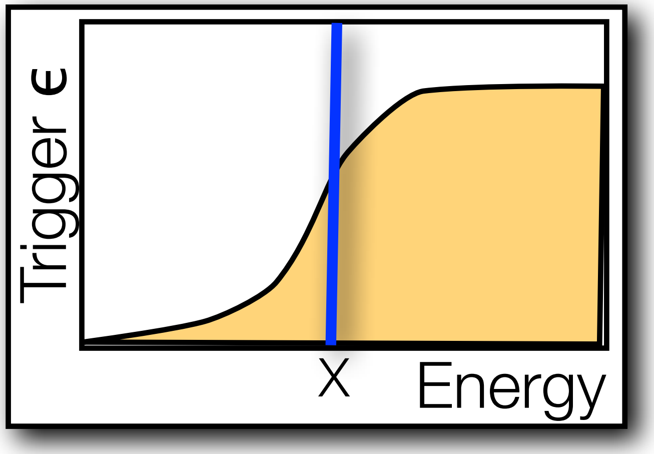
- When you use Monte Carlo (MC) in a model of triggered data, you need to be aware of trigger behaviors

Trigger Model

- When you use Monte Carlo (MC) in a model of triggered data, you need to be aware of trigger behaviors
- For instance, a trigger that turns on (fires) at energy X might in reality have a turn on like:

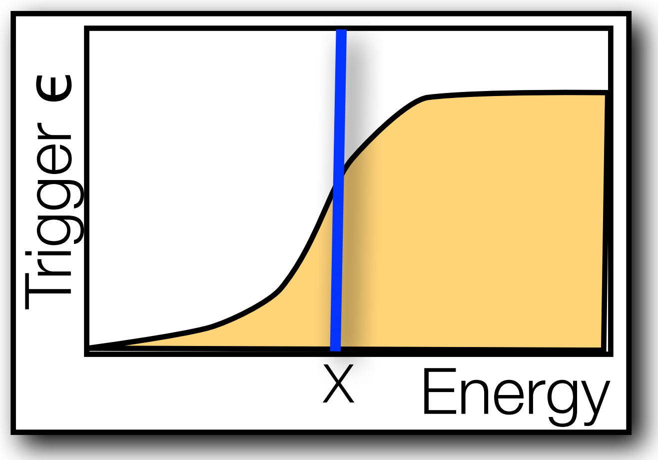
Trigger Model

- When you use Monte Carlo (MC) in a model of triggered data, you need to be aware of trigger behaviors
- For instance, a trigger that turns on (fires) at energy X might in reality have a turn on like:



Trigger Model

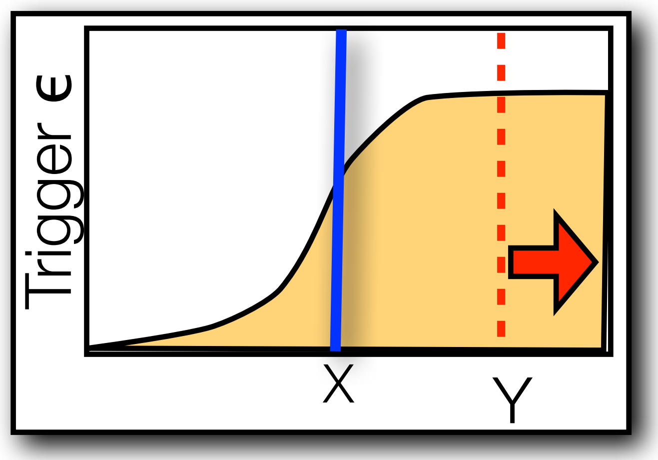
- When you use Monte Carlo (MC) in a model of triggered data, you need to be aware of trigger behaviors
- For instance, a trigger that turns on (fires) at energy X might in reality have a turn on like:



- There are two ways to account for this:

Trigger Model

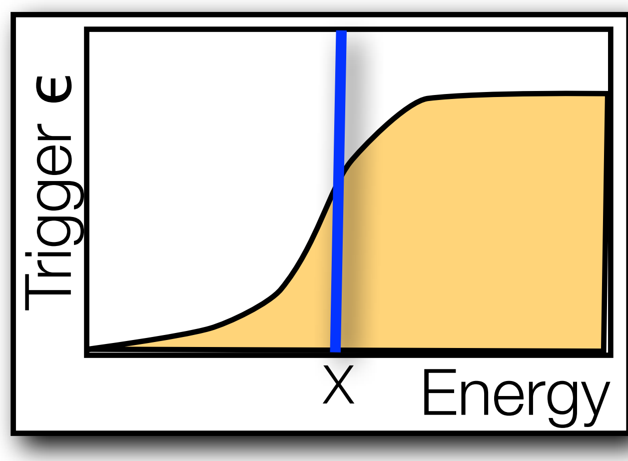
- When you use Monte Carlo (MC) in a model of triggered data, you need to be aware of trigger behaviors
- For instance, a trigger that turns on (fires) at energy X might in reality have a turn on like:



- There are two ways to account for this:
  - Have event requirement E > Y (where the trigger is fully efficient)
    - This hurts acceptance

Trigger Model

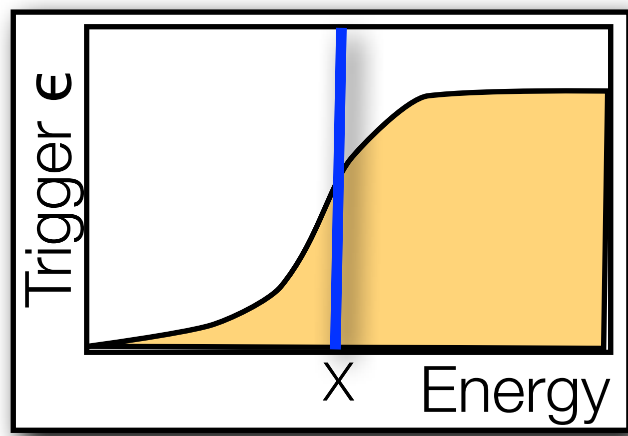
- When you use Monte Carlo (MC) in a model of triggered data, you need to be aware of trigger behaviors
- For instance, a trigger that turns on (fires) at energy X might in reality have a turn on like:



- There are two ways to account for this:
  - Have event requirement E > Y (where the trigger is fully efficient)
    - This hurts acceptance

Trigger Model

- When you use Monte Carlo (MC) in a model of triggered data, you need to be aware of trigger behaviors
- For instance, a trigger that turns on (fires) at energy X might in reality have a turn on like:



- There are two ways to account for this:
  - Have event requirement E > Y (where the trigger is fully efficient)
    - This hurts acceptance
  - Attempt to model the turn-on behavior
    - apply a weight to MC events corresponding probability it would fire any of our triggers

New Trigger

New Trigger

- Previous analysis considered two triggers:
  - Single electron candidate with track and largely EM energy deposited in **central** calorimeter ($E_T \geq 18$ GeV)
  - Two calorimeter deposits of at least 18 GeV largely EM in **central** or **forward** regions

New Trigger

- Previous analysis considered two triggers:
  - Single electron candidate with track and largely EM energy deposited in **central** calorimeter ($E_T \geq 18$ GeV)
  - Two calorimeter deposits of at least 18 GeV largely EM in **central** or **forward** regions
- A Higgs-motivated trigger was implemented in data taking $L_{int} \gtrsim 2.45$/fb
  - Two cal. deposits largely EM **central** or **forward**, $E_{T1,2}$>18, 9 GeV and $M_{ee} > 40$ GeV/c^2

New Trigger

- Previous analysis considered two triggers:
  - Single electron candidate with track and largely EM energy deposited in **central** calorimeter ($E_T \geq 18$ GeV)
  - Two calorimeter deposits of at least 18 GeV largely EM in **central** or **forward** regions
- A Higgs-motivated trigger was implemented in data taking $L_{int} \gtrsim 2.45$/fb
  - Two cal. deposits largely EM **central** or **forward**, $E_{T1,2}$>18, 9 GeV and $M_{ee} > 40$ GeV/c^2
- We needed to be able to model the “OR” probability of the combined three triggers

New Trigger

- Previous analysis considered two triggers:
  - Single electron candidate with track and largely EM energy deposited in **central** calorimeter ($E_T \geq 18$ GeV)
  - Two calorimeter deposits of at least 18 GeV largely EM in **central** or **forward** regions
- A Higgs-motivated trigger was implemented in data taking $L_{int} \gtrsim 2.45$/fb
  - Two cal. deposits largely EM **central** or **forward**, $E_{T1,2}$>18, 9 GeV and $M_{ee} > 40$ GeV/c^2
- We needed to be able to model the "OR" probability of the combined three triggers
  - Proposed solution: model its efficiency with a neural network

Trigger Model

Trigger Model

- We want to parameterize how likely a given Z event is to fire one of our triggers
- We need unbiased sample of Z events containing

Trigger Model

- We want to parameterize how likely a given Z event is to fire one of our triggers
- We need unbiased sample of Z events containing
  - one subset of events that fired at least one of our triggers

Trigger Model

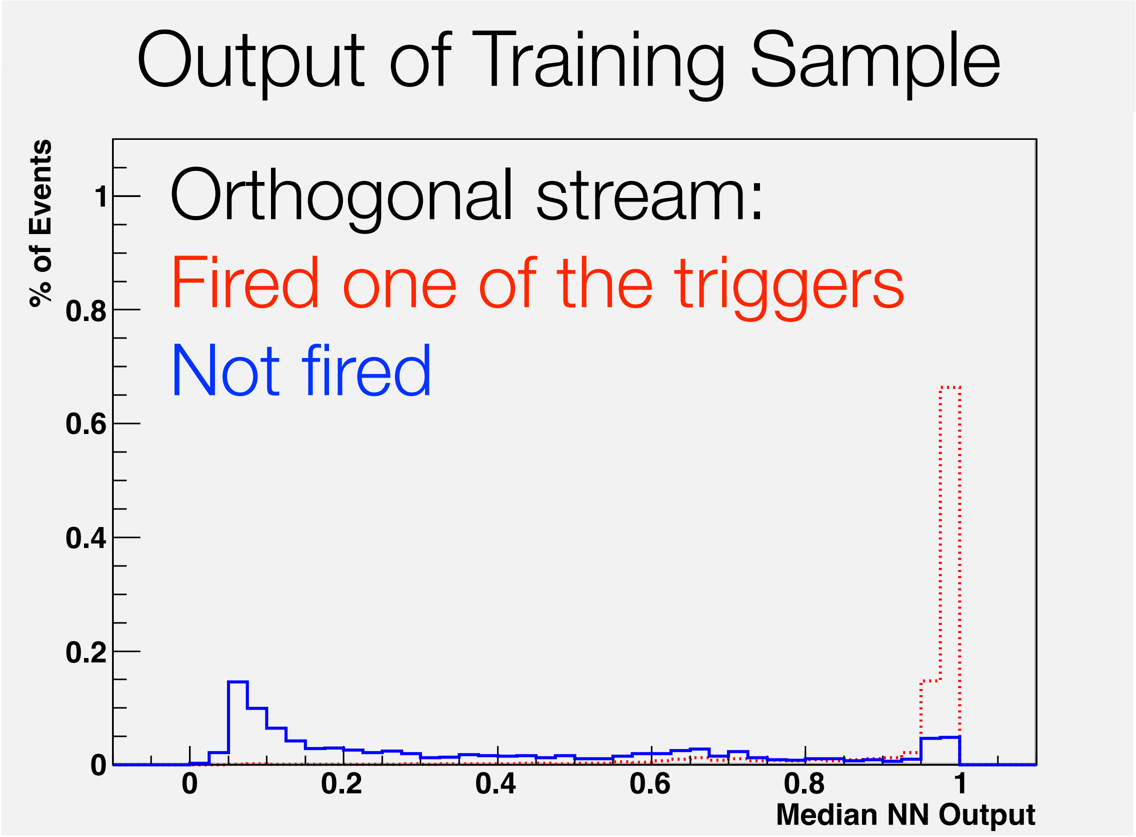
- We want to parameterize how likely a given Z event is to fire one of our triggers
- We need unbiased sample of Z events containing
  - one subset of events that fired at least one of our triggers
  - another subset that did not fire any of our triggers

Trigger Model

- We want to parameterize how likely a given Z event is to fire one of our triggers
- We need unbiased sample of Z events containing
  - one subset of events that fired at least one of our triggers
  - another subset that did not fire any of our triggers
- For this, we used an independent data stream (saved for its MET characteristics)
  - Trained using variables: $\Delta R(e_1,e_2)$, M_{ee}, electron energies, track p_Ts, η_{det}s, L_{shr}, and Had/Ems

Trigger Model

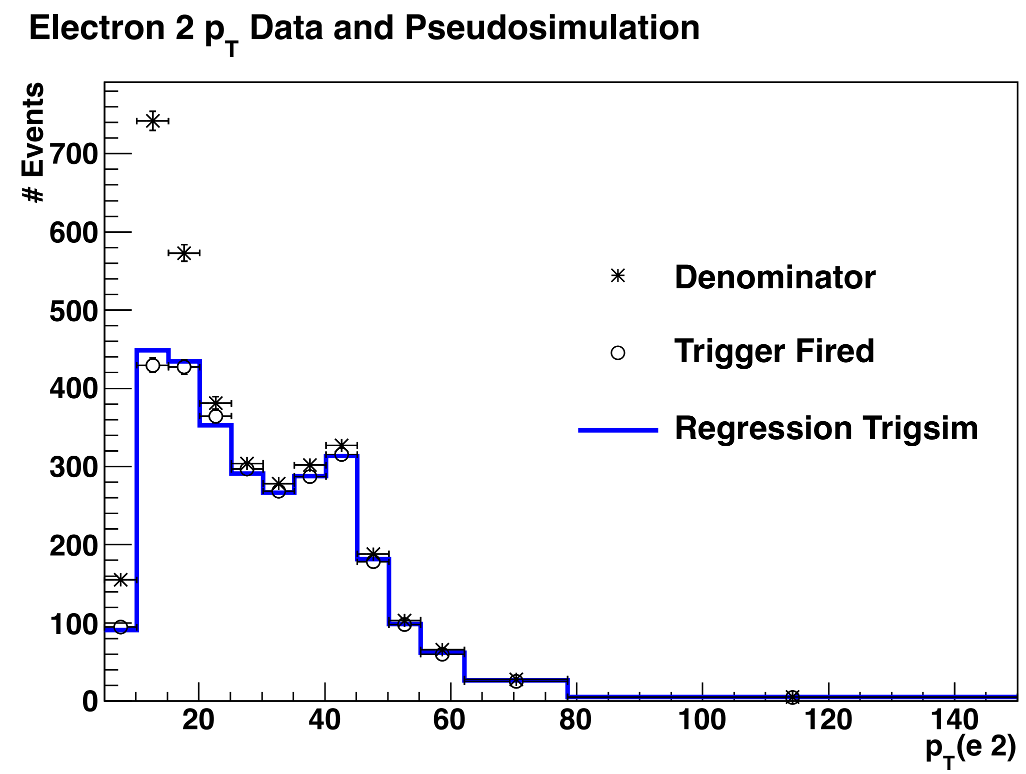
- We want to parameterize how likely a given Z event is to fire one of our triggers
- We need unbiased sample of Z events containing
  - one subset of events that fired at least one of our triggers
  - another subset that did not fire any of our triggers
- For this, we used an independent data stream (saved for its MET characteristics)
  - Trained using variables: $\Delta R(e_1,e_2)$, M_{ee}, electron energies, track p_Ts, η_{det}s, L_{shr}, and Had/Ems
- From network, determine weight, w:



Trigger Model Check

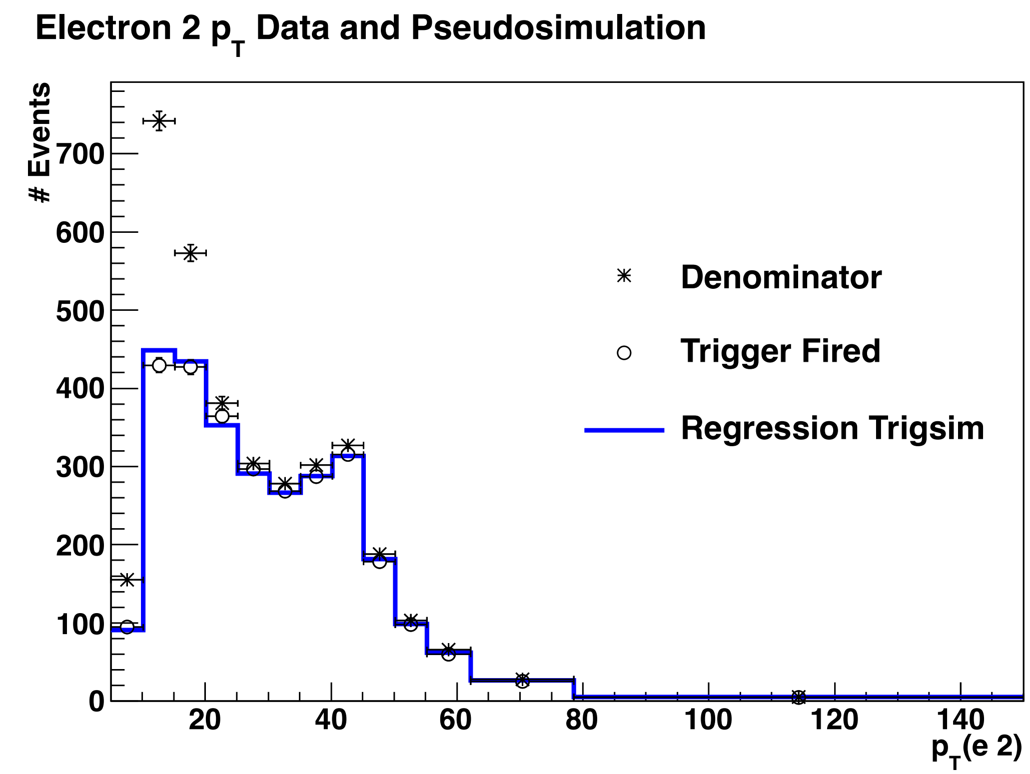
Trigger Model Check

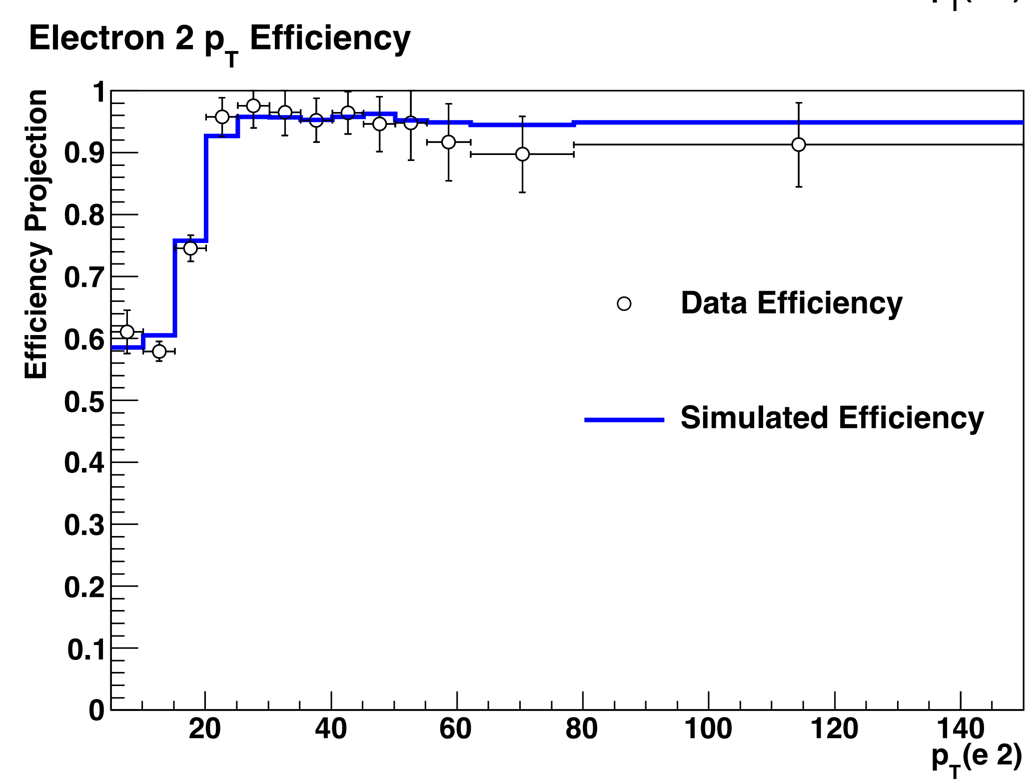
- Consistency check in data, for instance P_T of the second electron
  - denominator = Z events in MET triggered stream
  - o = Z events in MET triggered stream that fired one of the 3 electron triggers
  - -- = Z events in MET stream with regression trigger weight applied



Trigger Model Check

- Consistency check in data, for instance P_T of the second electron
    - denominator = Z events in MET triggered stream
    - o = Z events in MET triggered stream that fired one of the 3 electron triggers
    - -- = Z events in MET stream with regression trigger weight applied
- We can divide these & get an efficiency, ε
    - denominator is all Z events in MET triggered stream
    - ε follows the expected behavior



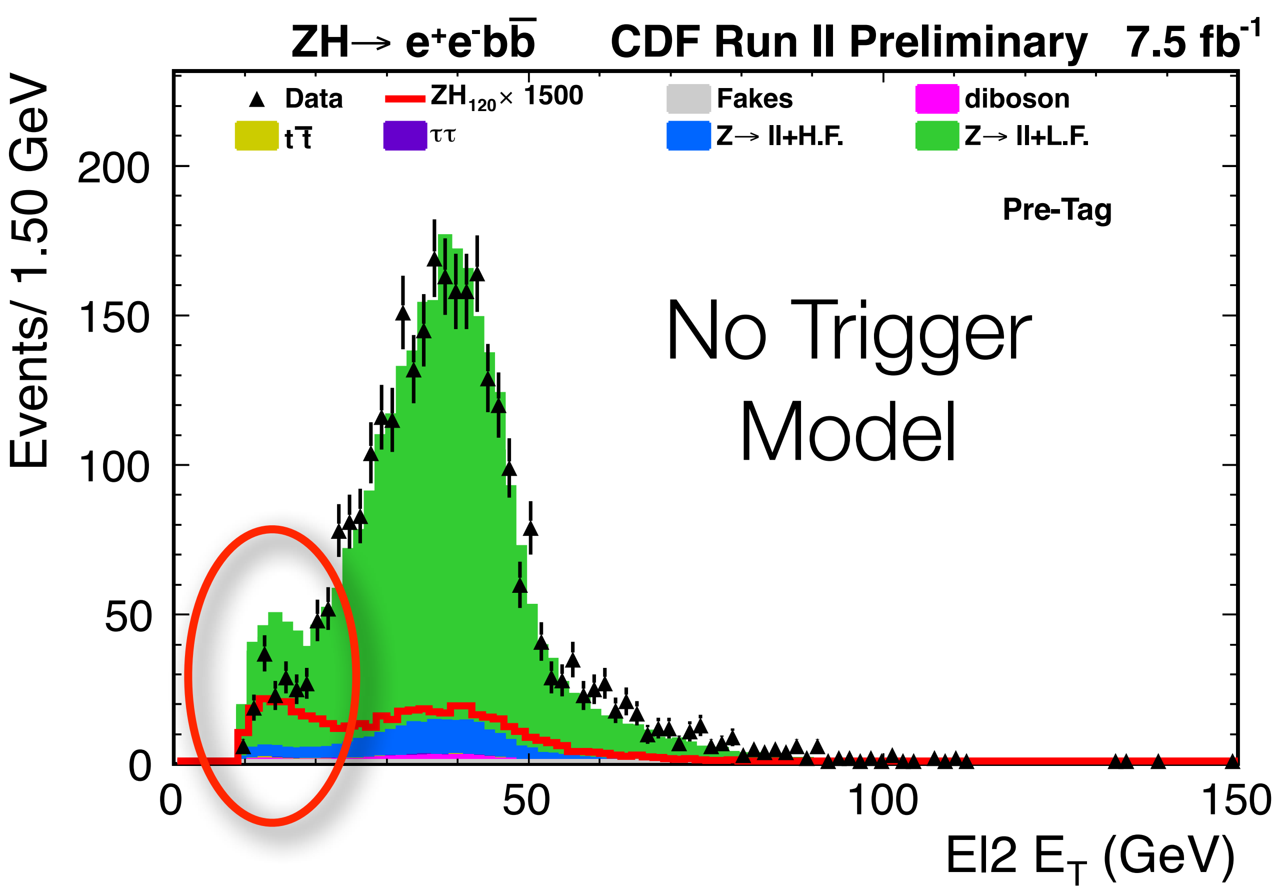


Trigger Model Check: Monte Carlo

- Applying the trigger model improved modeling
  - Plots are of the sub-leading electron E_T in events with two forward electrons

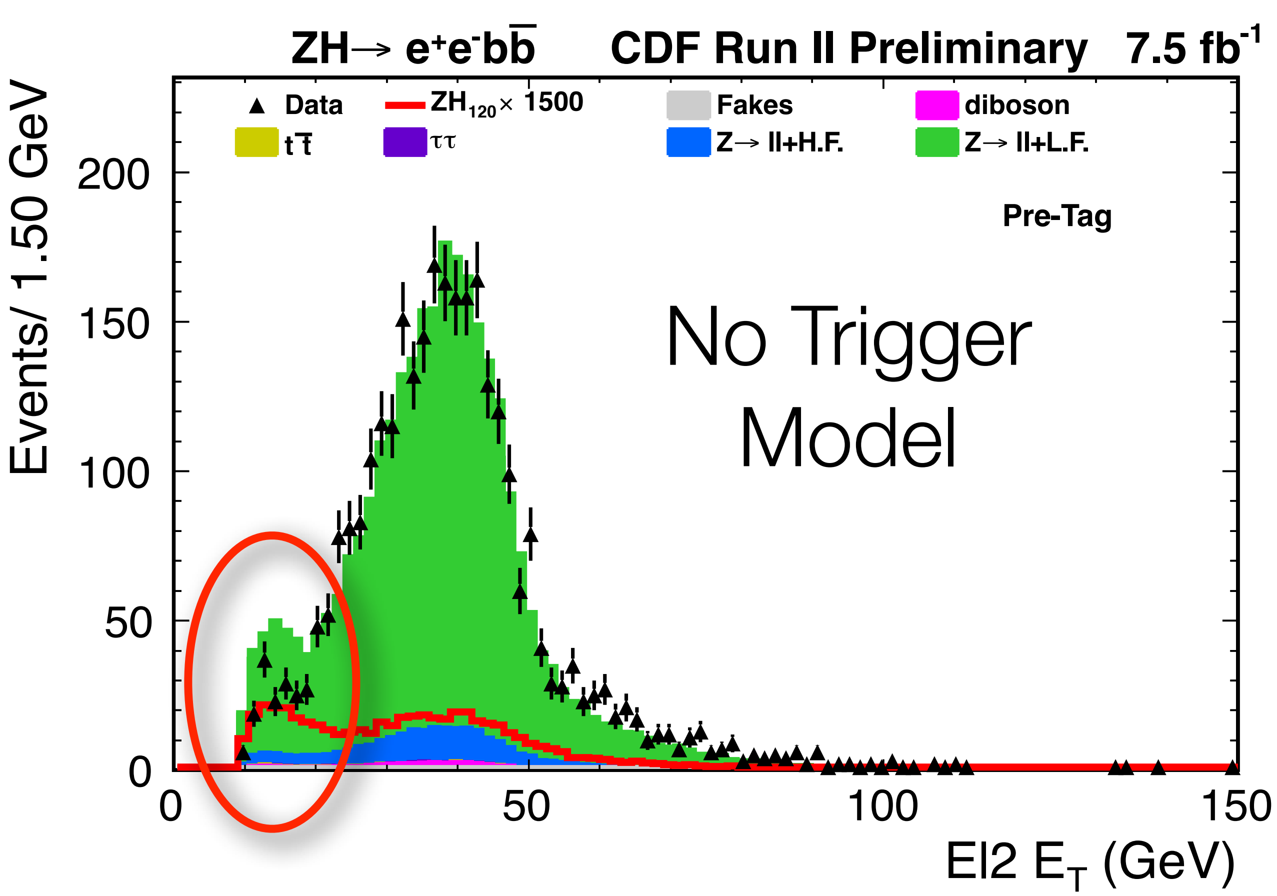
Trigger Model Check: Monte Carlo

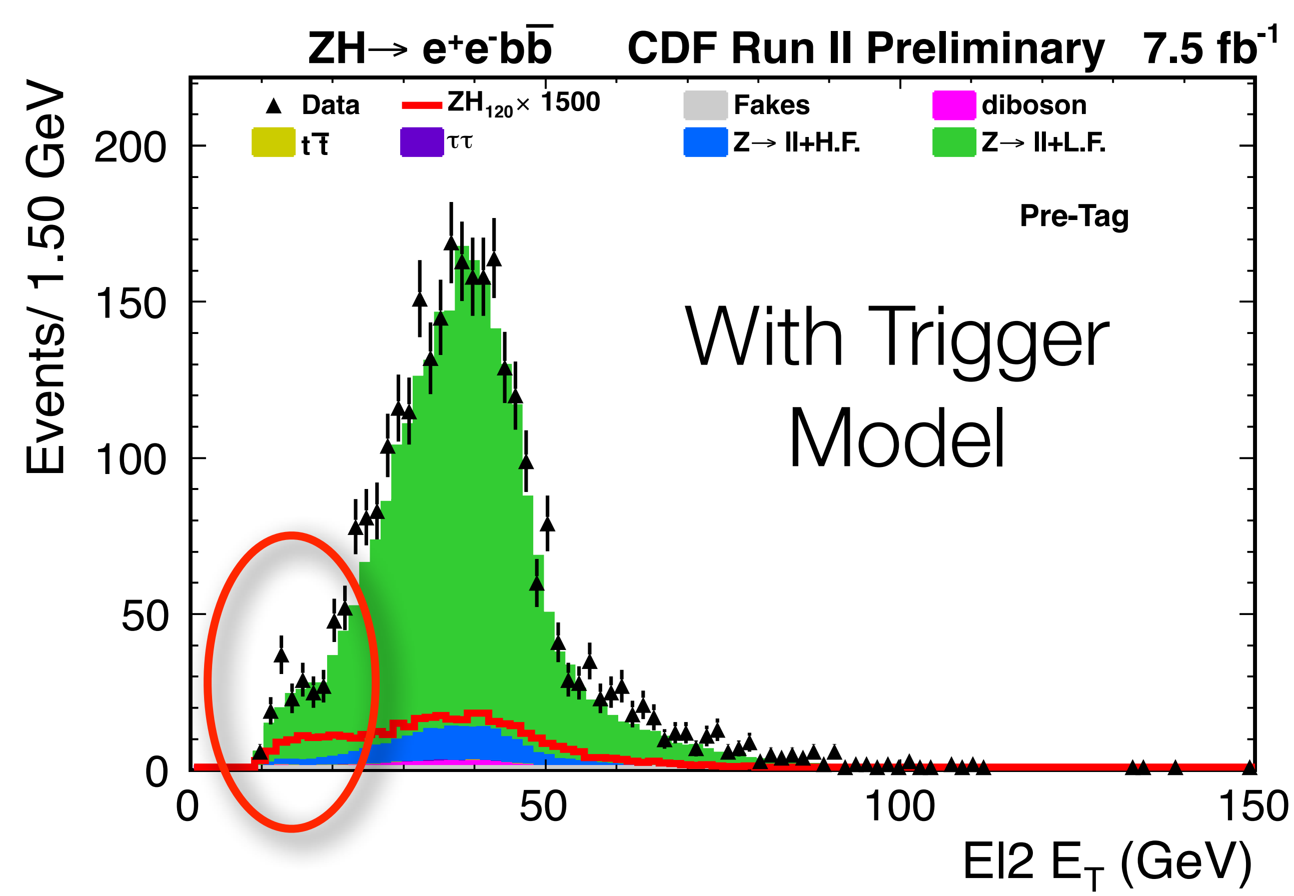
- Applying the trigger model improved modeling
    - Plots are of the sub-leading electron E_T in events with two forward electrons



Trigger Model Check: Monte Carlo

- Applying the trigger model improved modeling
  - Plots are of the sub-leading electron E_T in events with two forward electrons





Changing Gears: On to Electron ID!

Goal is to train a neural network to separate real electrons from fake electrons with a higher efficiency than has been done in the past

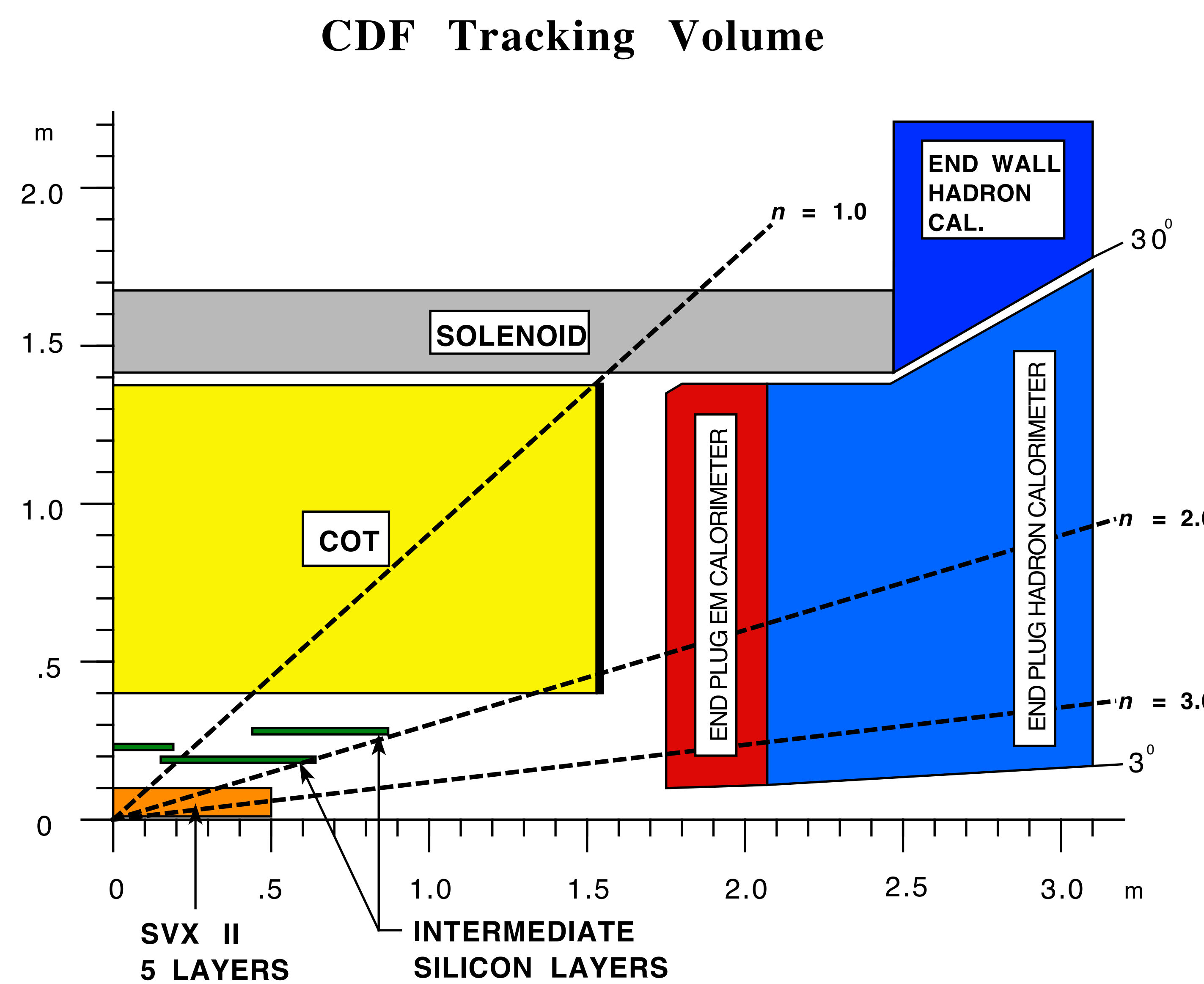
Further Acceptance: Electron Identification

Further Acceptance: Electron Identification

- Previous analysis used a cut-based electron selection

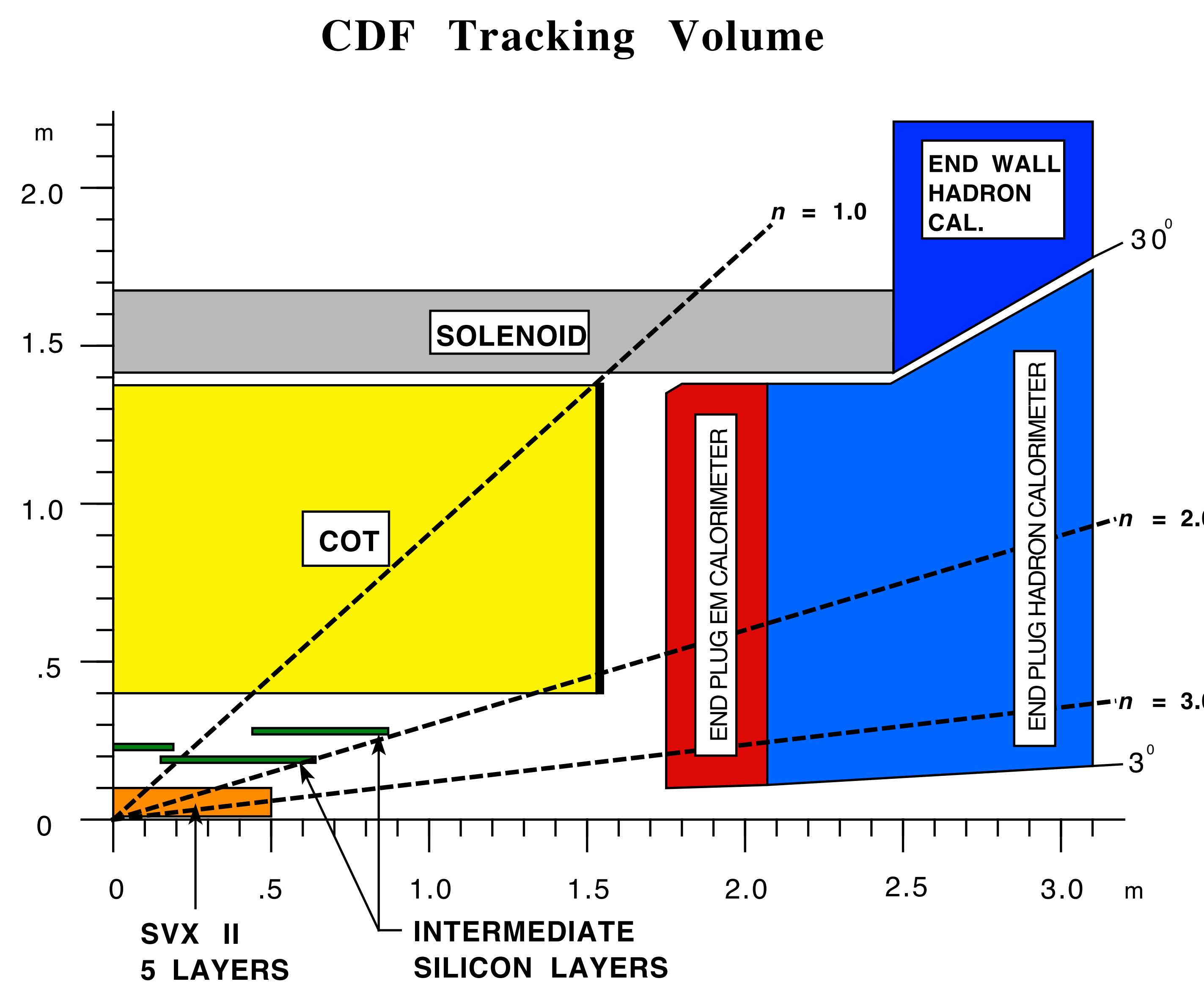
Further Acceptance: Electron Identification

- Previous analysis used a cut-based electron selection
- Developed a single-electron ID



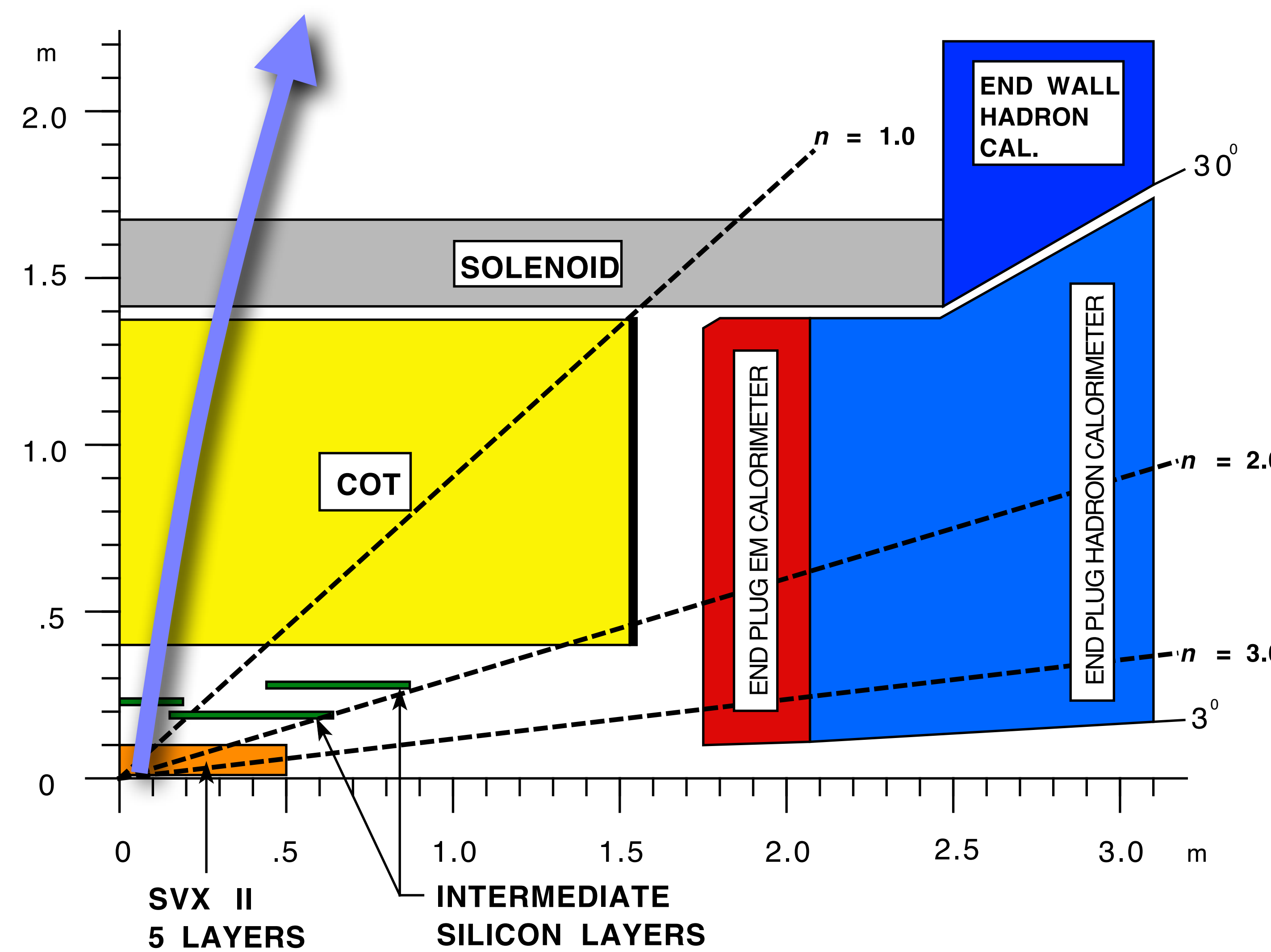
Further Acceptance: Electron Identification

- Previous analysis used a cut-based electron selection
- Developed a <u>single-electron ID</u>
- Different kinds/quality of electrons motivated 3 different networks:



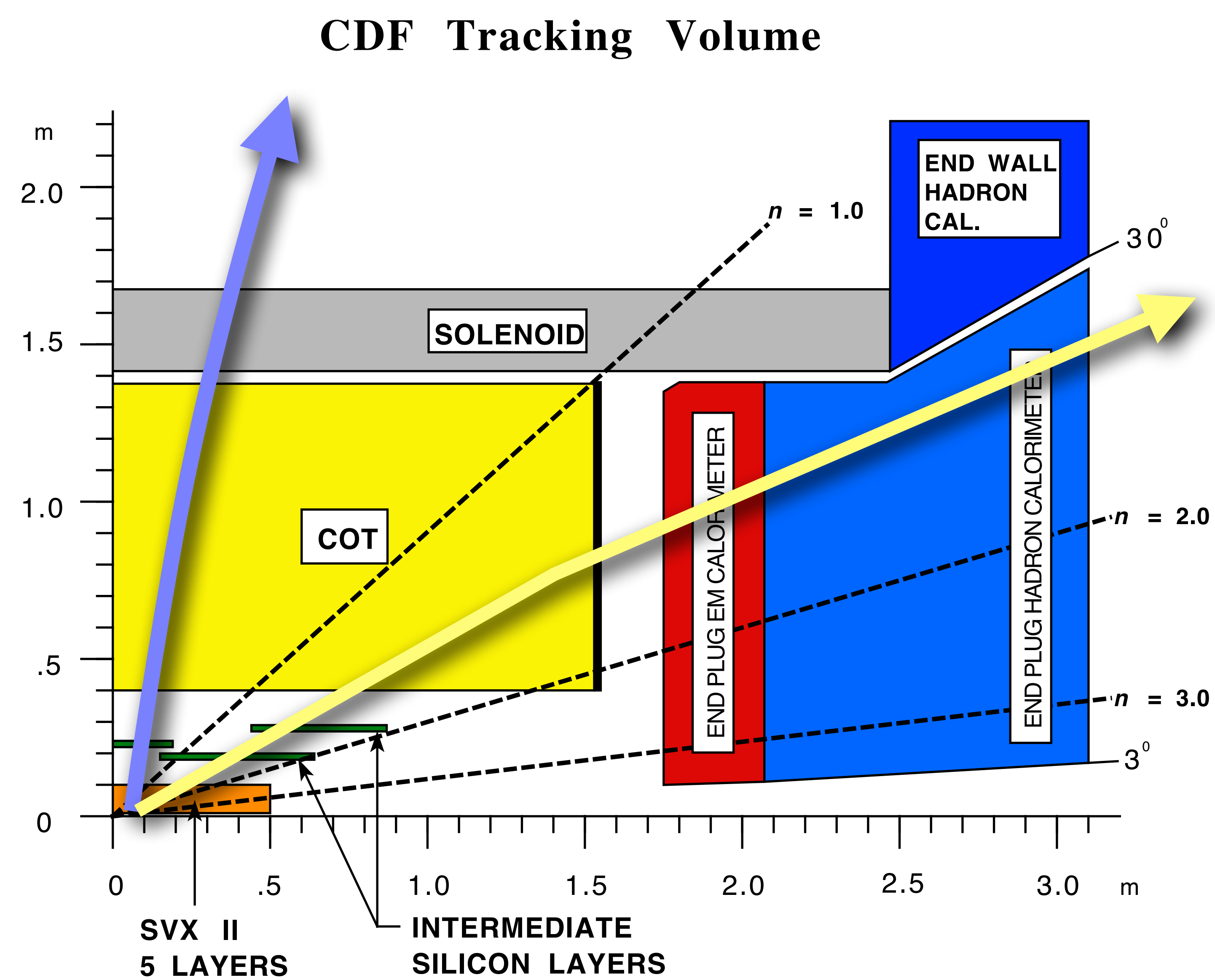
Further Acceptance: Electron Identification

- Previous analysis used a cut-based electron selection
- Developed a single-electron ID
- Different kinds/quality of electrons motivated 3 different networks:
    - central (|η|<1.1)



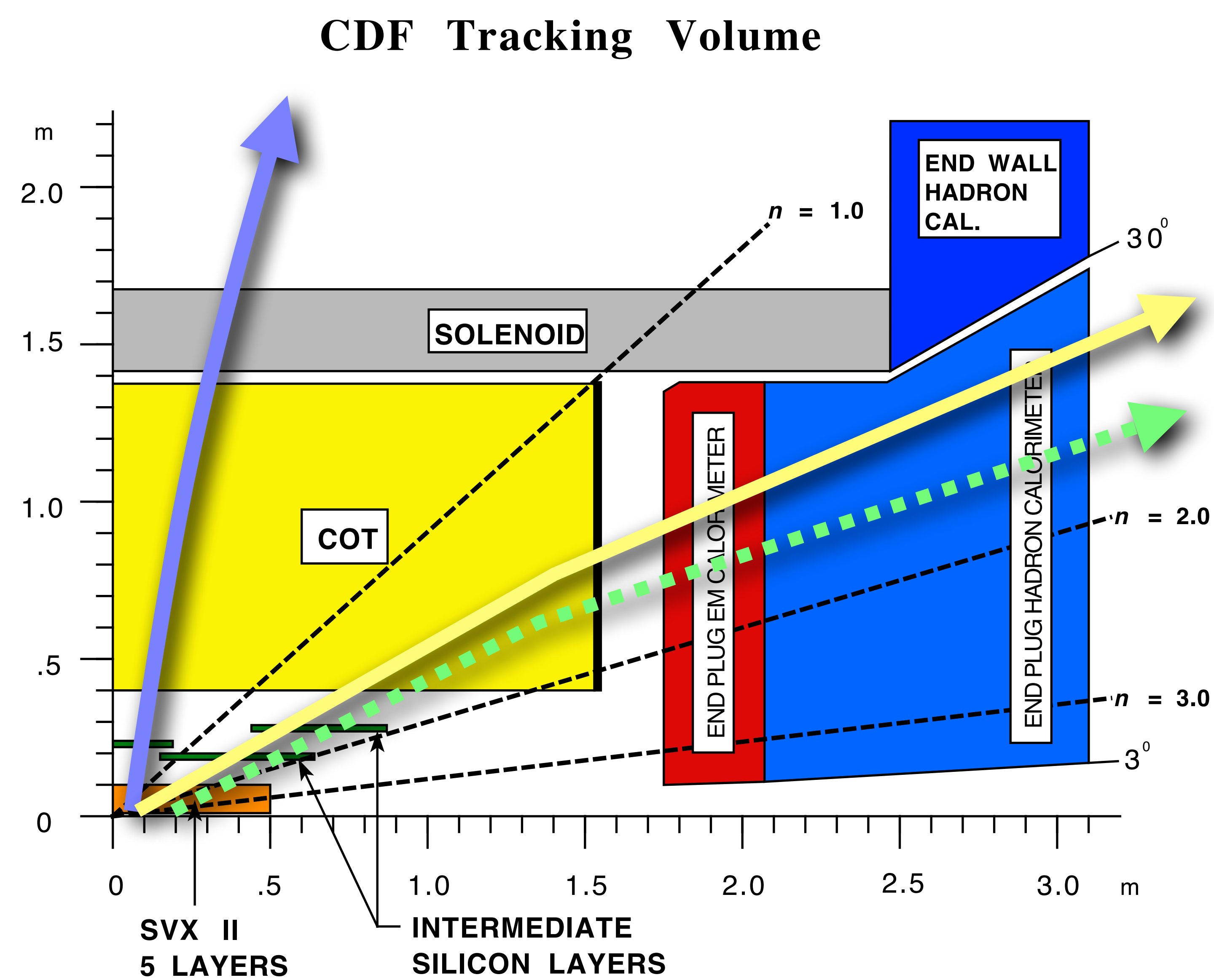
Further Acceptance: Electron Identification

- Previous analysis used a cut-based electron selection
- Developed a <u>single-electron ID</u>
- Different kinds/quality of electrons motivated 3 different networks:
  - central ($|\eta|<1.1$)
  - forward with Si-based track (**phoenix**) ($|\eta|>1.1$)



Further Acceptance: Electron Identification

- Previous analysis used a cut-based electron selection
- Developed a single-electron ID
- Different kinds/quality of electrons motivated 3 different networks:
  - central (|η|<1.1)
  - forward with Si-based track (**phoenix**) (|η|>1.1)
  - forward without Si-based track (1.2<|η|<2.8)



Training Precursors

Training Precursors

- First, define trigger-inspired pre-selection cuts
  - so that we only train to find electrons realistically saved in data

Training Precursors

- First, define trigger-inspired pre-selection cuts
  - so that we only train to find electrons realistically saved in data

Category	η	EmEt (GeV)	Had/Em	Additional
Central	$\lvert\eta\rvert < 1.1$	> 9	< 0.125	
Forward Phoenix	$\lvert\eta\rvert > 1.1$	> 9	< 0.0625	
Forward Non-Phoenix	$1.2 < \lvert\eta\rvert < 2.8$	> 9	< 0.125	Momentum Defined

Training Precursors

- First, define trigger-inspired pre-selection cuts
  - so that we only train to find electrons realistically saved in data

Category	η	EmEt (GeV)	Had/Em	Additional
Central	$\lvert\eta\rvert < 1.1$	> 9	< 0.125	
Forward Phoenix	$\lvert\eta\rvert > 1.1$	> 9	< 0.0625	
Forward Non-Phoenix	$1.2 < \lvert\eta\rvert < 2.8$	> 9	< 0.125	Momentum Defined

  - Additionally, the track z_0 must be well contained in the detector ($|z_0|$<60cm)

Training Precursors

- First, define trigger-inspired pre-selection cuts
  - so that we only train to find electrons realistically saved in data

Category	η	EmEt (GeV)	Had/Em	Additional
Central	$\lvert\eta\rvert < 1.1$	> 9	< 0.125	
Forward Phoenix	$\lvert\eta\rvert > 1.1$	> 9	< 0.0625	
Forward Non-Phoenix	$1.2 < \lvert\eta\rvert < 2.8$	> 9	< 0.125	Momentum Defined

  - Additionally, the track z_0 must be well contained in the detector ($|z_0|$<60cm)

- Then, consider signal and background templates (mc, data?)
- What variables to use?

How to Train?

How to Train?

- Considered templates:
- Considered variables:

How to Train?

- Considered templates:
    - Signal:
        - 1) generator-level e's in Z+lf MC,
        - 2) data probe leg(tag-and-probe $76<=m_{ee}<=106$)
- Considered variables:

How to Train?

- Considered templates:
  - Signal:
    - 1) generator-level e's in Z+lf MC,
    - 2) data probe leg(tag-and-probe $76 <= m_{ee} <= 106$)
  - Background:
    - 1) hegp-matched non-electrons in Z+lf MC and W+jets MC,
    - 2) data electrons candidates outside of Z window,
    - 3) data electron candidates in jet-triggered data with exactly one candidate (Z veto) and MET<15 GeV (W veto)
- Considered variables:

How to Train?

- Considered templates:
  - Signal:
    - 1) generator-level e's in Z+lf MC,
    - 2) data probe leg(tag-and-probe $76 <= m_{ee} <= 106$)
  - Background:
    - 1) hegp-matched non-electrons in Z+lf MC and W+jets MC,
    - 2) data electrons candidates outside of Z window,
    - 3) data electron candidates in jet-triggered data with exactly one candidate (Z veto) and MET<15 GeV (W veto)

- Considered variables:
  - Used an iterative method to select the most powerful variables out of a pool (later slide)
  - Had a pool of variables including energy-type values (p_T, energy, *etc*.)
  - Another pool without -- only quality-type variables (Had/Em, track χ^2, E/P, *etc*.)

How to Train?

- Considered templates:
  - Signal:
    - 1) generator-level e's in Z+lf MC,
    - 2) data probe leg(tag-and-probe $76 <= m_{ee} <= 106$)
  - Background:
    - 1) hegp-matched non-electrons in Z+lf MC and W+jets MC,
    - 2) data electrons candidates outside of Z window,
    - 3) data electron candidates in jet-triggered data with exactly one candidate (Z veto) and MET<15 GeV (W veto)

- Considered variables:
  - Used an iterative method to select the most powerful variables out of a pool (later slide)
  - Had a pool of variables including energy-type values (p_T, energy, *etc*.)
  - Another pool without -- only quality-type variables (Had/Em, track χ^2, E/P, *etc*.)

- Compared networks to cut-based selections & evaluated based on cleanness and improvement in acceptance

How to Train?

- Considered templates:
  - Signal:
    - All: 1) generator-level e's in Z+lf MC,
    - 2) data probe leg(tag-and-probe $76 <= m_{ee} <= 106$)
  - Background:
    - 1) hegp-matched non-electrons in Z+lf MC and W+jets MC,
    - Central: 2) data electrons candidates outside of Z window,
    - Both Forward: 3) data electron candidates in jet-triggered data with exactly one candidate (Z veto) and MET<15 GeV (W veto)

- Considered variables:
  - Used an iterative method to select the most powerful variables out of a pool (later slide)
  - Had a pool of variables including energy-type values (p_T, energy, *etc*.)
  - Another pool without -- only quality-type variables (Had/Em, track χ^2, E/P, *etc*.)

- Compared networks to cut-based selections & evaluated based on cleanness and improvement in acceptance

How to Select Variables

How to Select Variables

- Variables were selected using an iterative approach. Given a pool of N variables

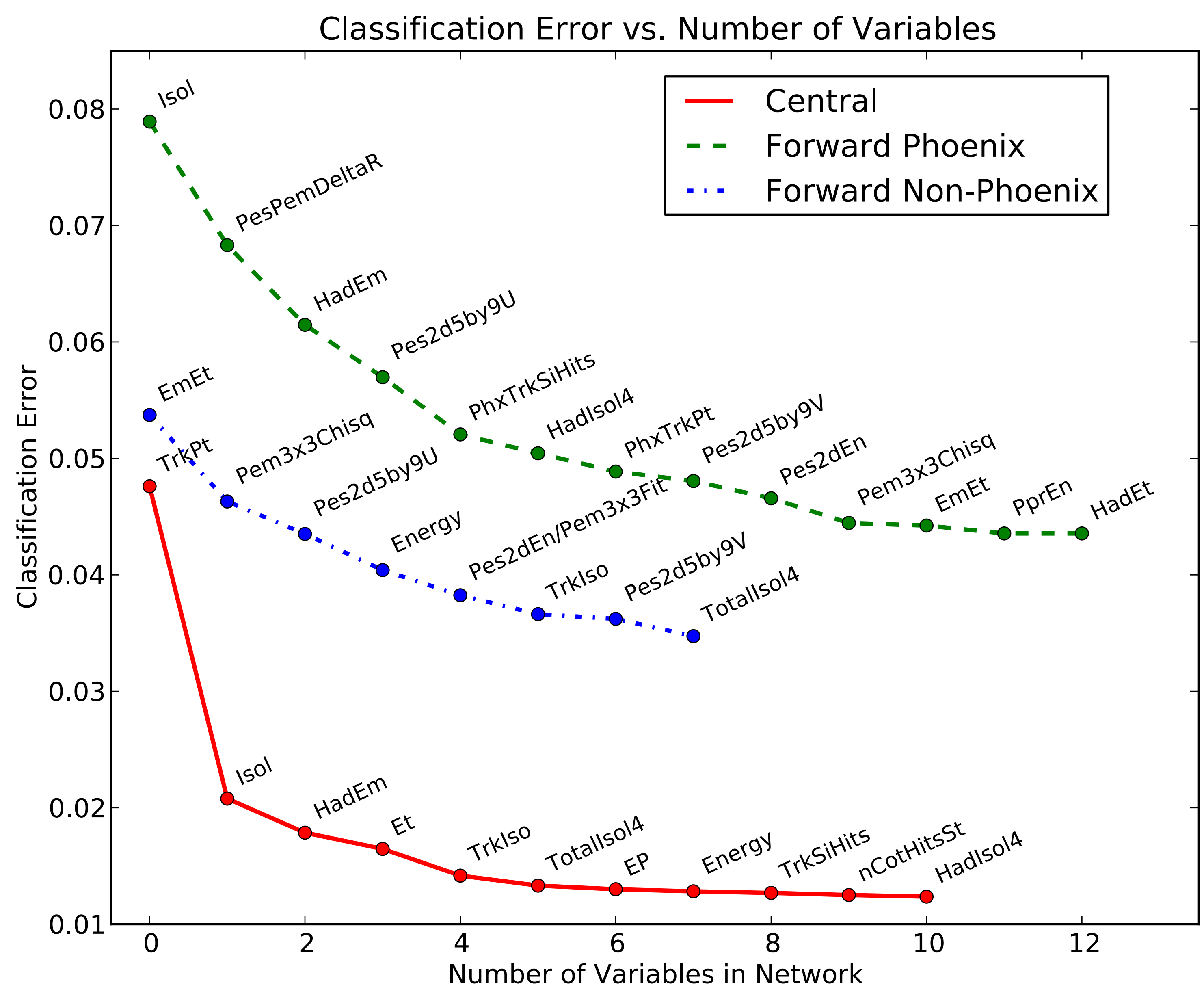
How to Select Variables

- Variables were selected using an iterative approach. Given a pool of N variables
  - Remove poorly modeled variables

$$\sigma = \frac{1}{2} \sum_{i}^{events} (target_i - score_i)^2$$

How to Select Variables

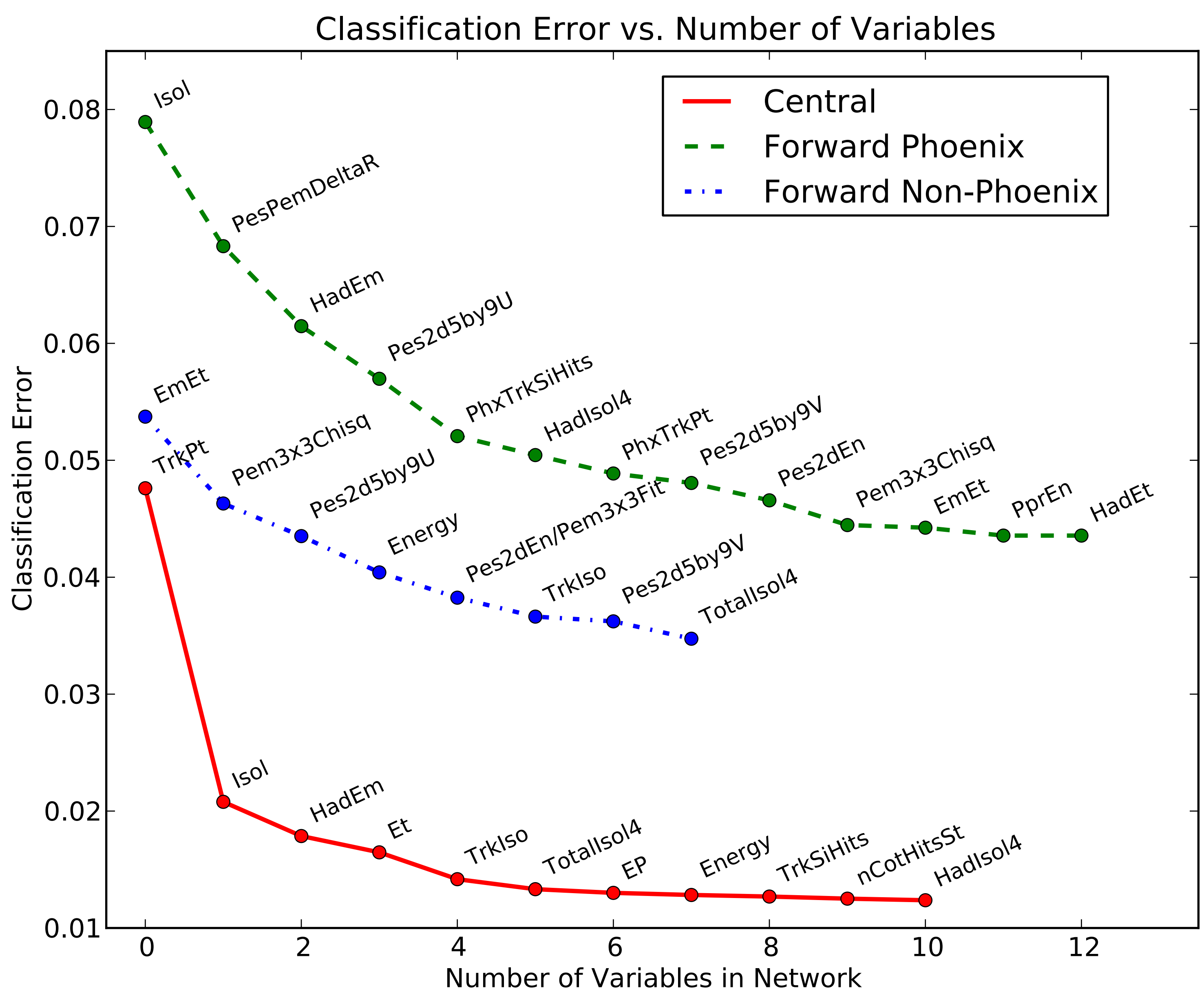
- Variables were selected using an iterative approach. Given a pool of N variables
  - Remove poorly modeled variables
  - N, 1-variables networks are created and evaluated. The most powerful (smallest testing error) variable is retained
  - N-1 2-variable networks are created and evaluated using the var. from step 1 + one from the pool



$$\sigma = \frac{1}{2} \sum_{i}^{events} (target_i - score_i)^2$$

How to Select Variables

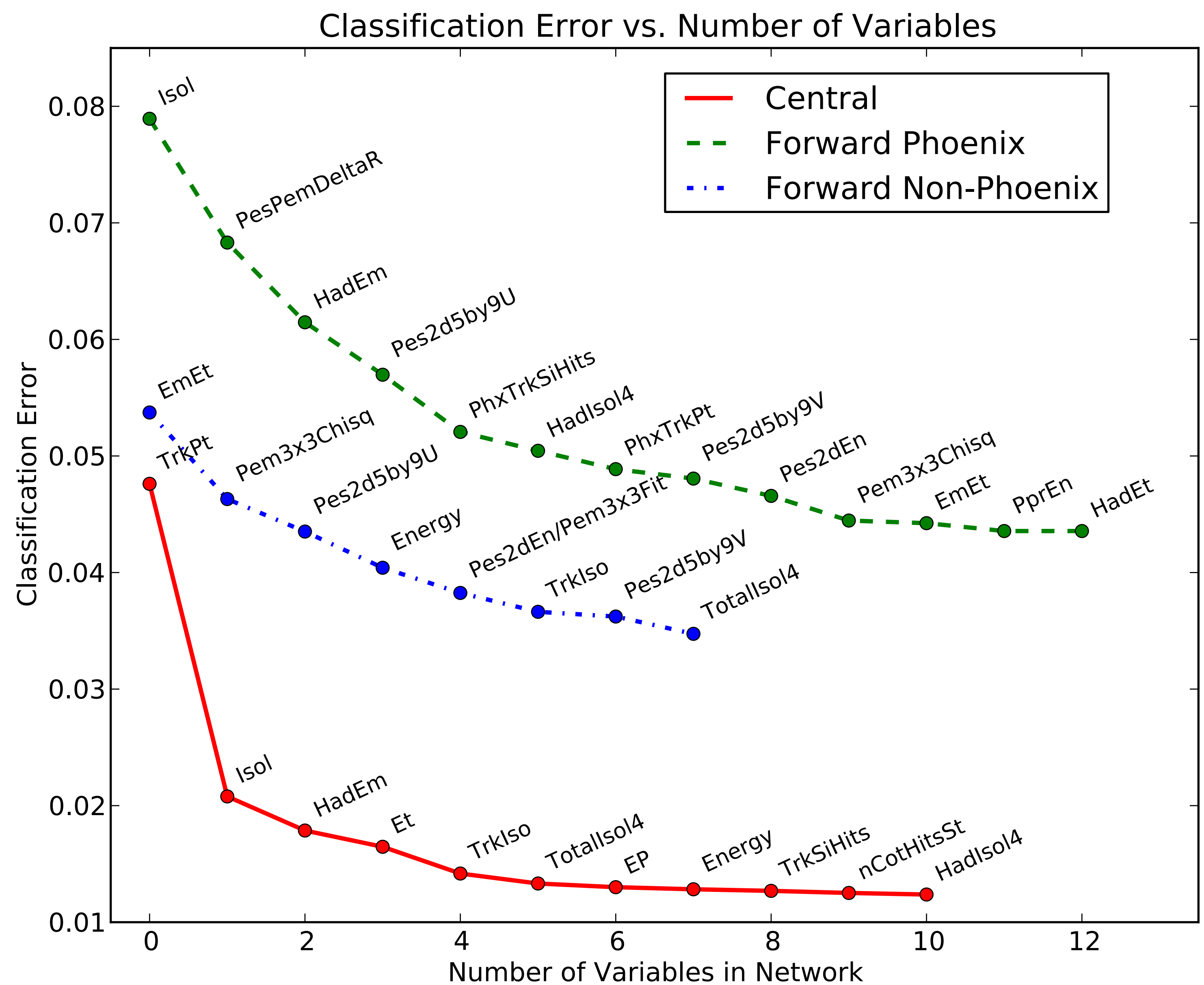
- Variables were selected using an iterative approach. Given a pool of N variables
    - Remove poorly modeled variables
    - N, 1-variables networks are created and evaluated. The most powerful (smallest testing error) variable is retained
    - N-1 2-variable networks are created and evaluated using the var. from step 1 + one from the pool
    - ⋮



$$\sigma = \frac{1}{2} \sum_{i}^{events} (target_i - score_i)^2$$

How to Select Variables

- Variables were selected using an iterative approach. Given a pool of N variables
  - Remove poorly modeled variables
  - N, 1-variables networks are created and evaluated. The most powerful (smallest testing error) variable is retained
  - N-1 2-variable networks are created and evaluated using the var. from step 1 + one from the pool
  - ⋮
  - This continues until the testing error is no longer reduced



$$\sigma = \frac{1}{2} \sum_{i}^{events} (target_i - score_i)^2$$

Variables Selected

Central:

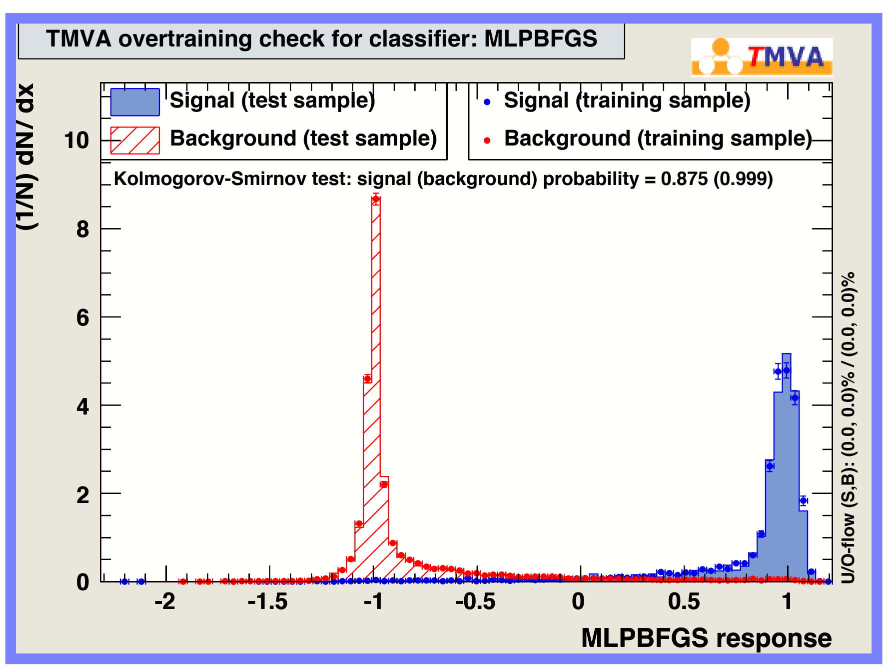
- Track P_T
- Isolation Ratio
- Had./Em.
- Track Isolation
- Total Cal. Isolation (R=.4)
- E/P
- Energy
- Silicon Hits

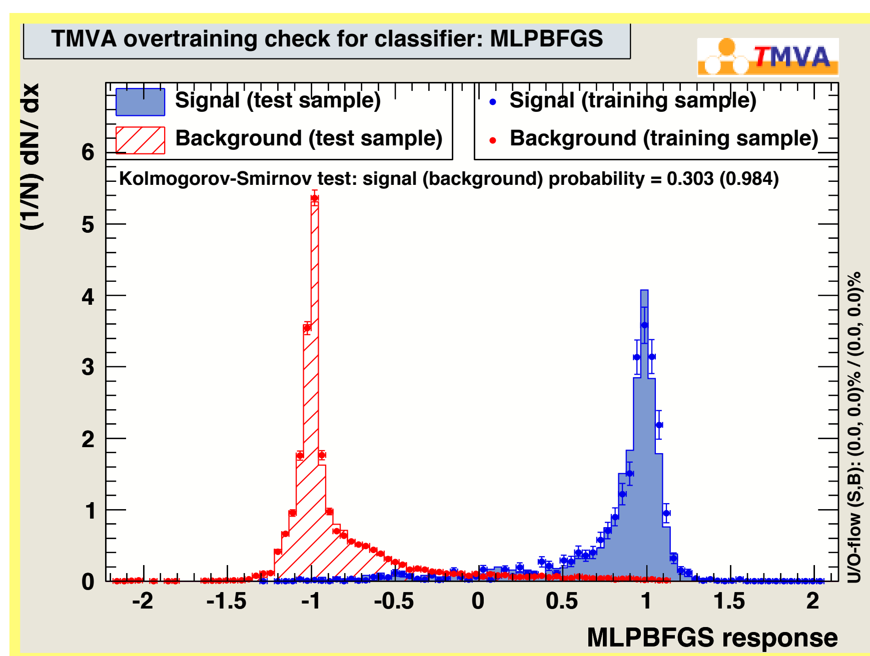
Plug Phoenix

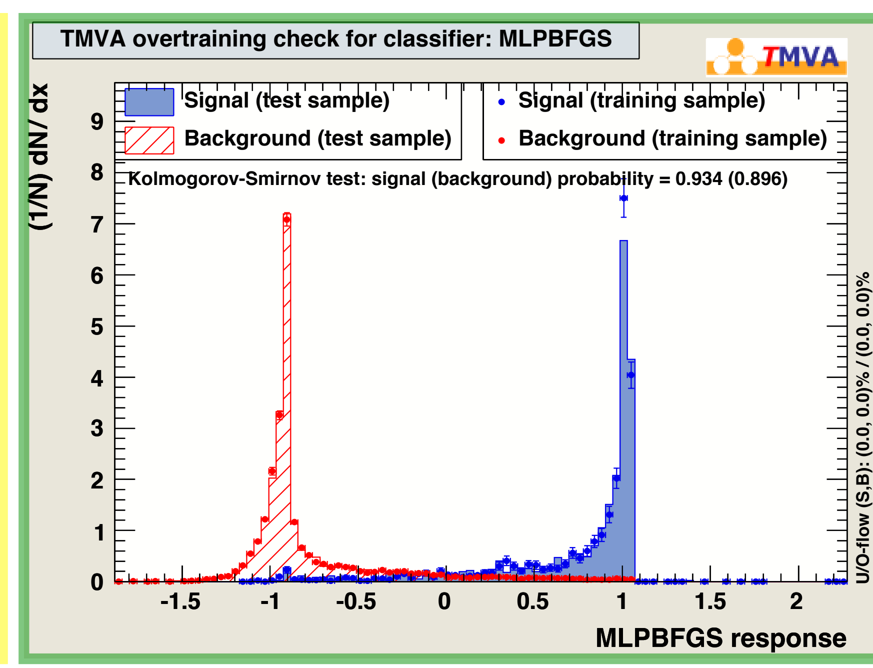
- Isolation Ratio
- Pes Pem ΔR
- Had./Em.
- Pes 2d 5×9 U
- Silicon Hits
- Had. Isol. (R=.4)
- Track P_T
- Pes 2d 5×9 V
- Pes 2d Energy
- Pem 3×3 ChiSq.
- Em. E_T
- Plug Preradiator Energy
- Had. E_T

Plug Non-Phoenix

- Em. E_T
- Pem 3×3 Chisq
- Pes 2d 5×9 U
- Energy
- Pes 2d Energy
- Track Isolation
- Pes 2d 5by9 V
- Total Cal. Isolation (R=.4)







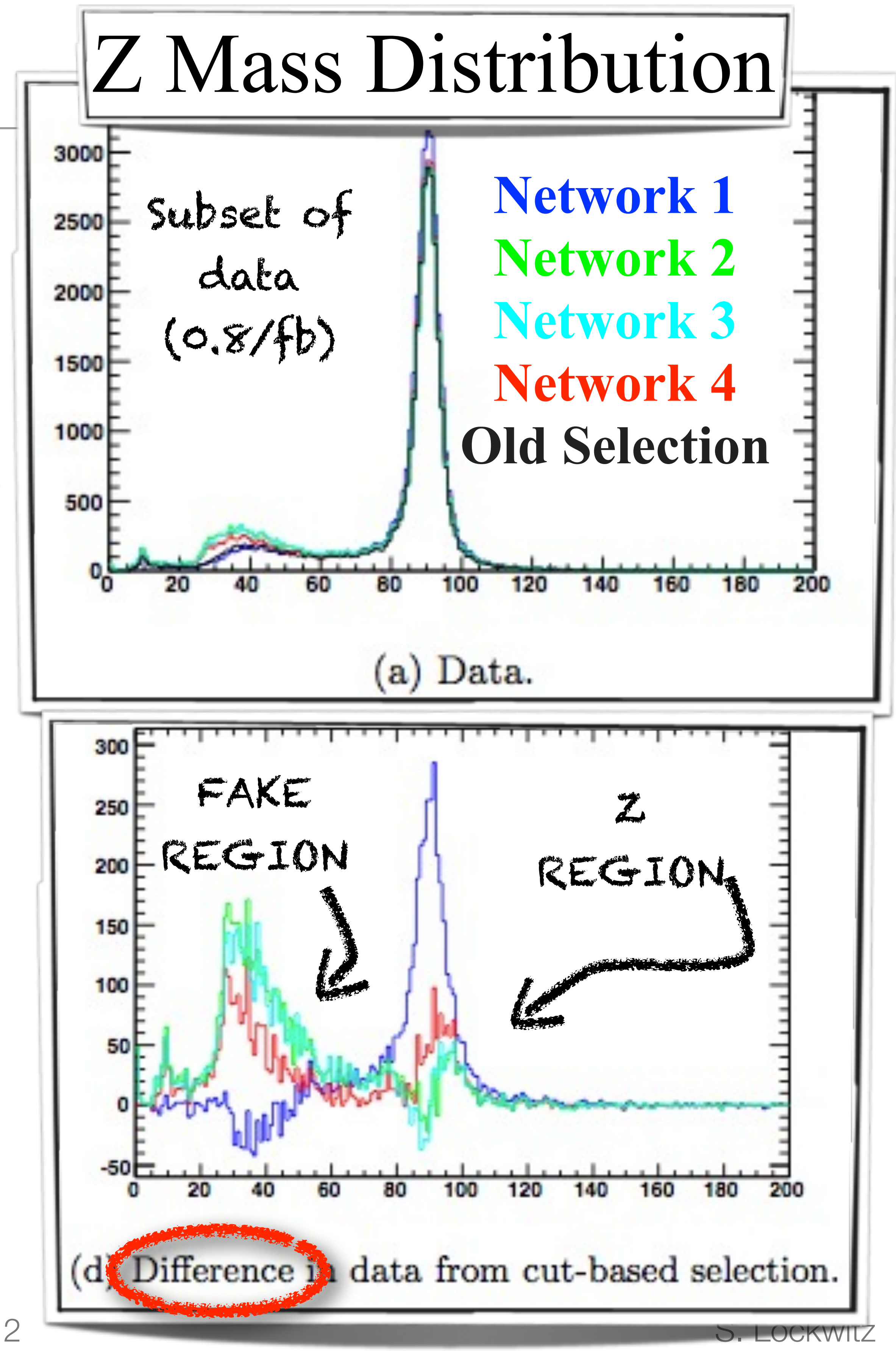
Making Z's

Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value

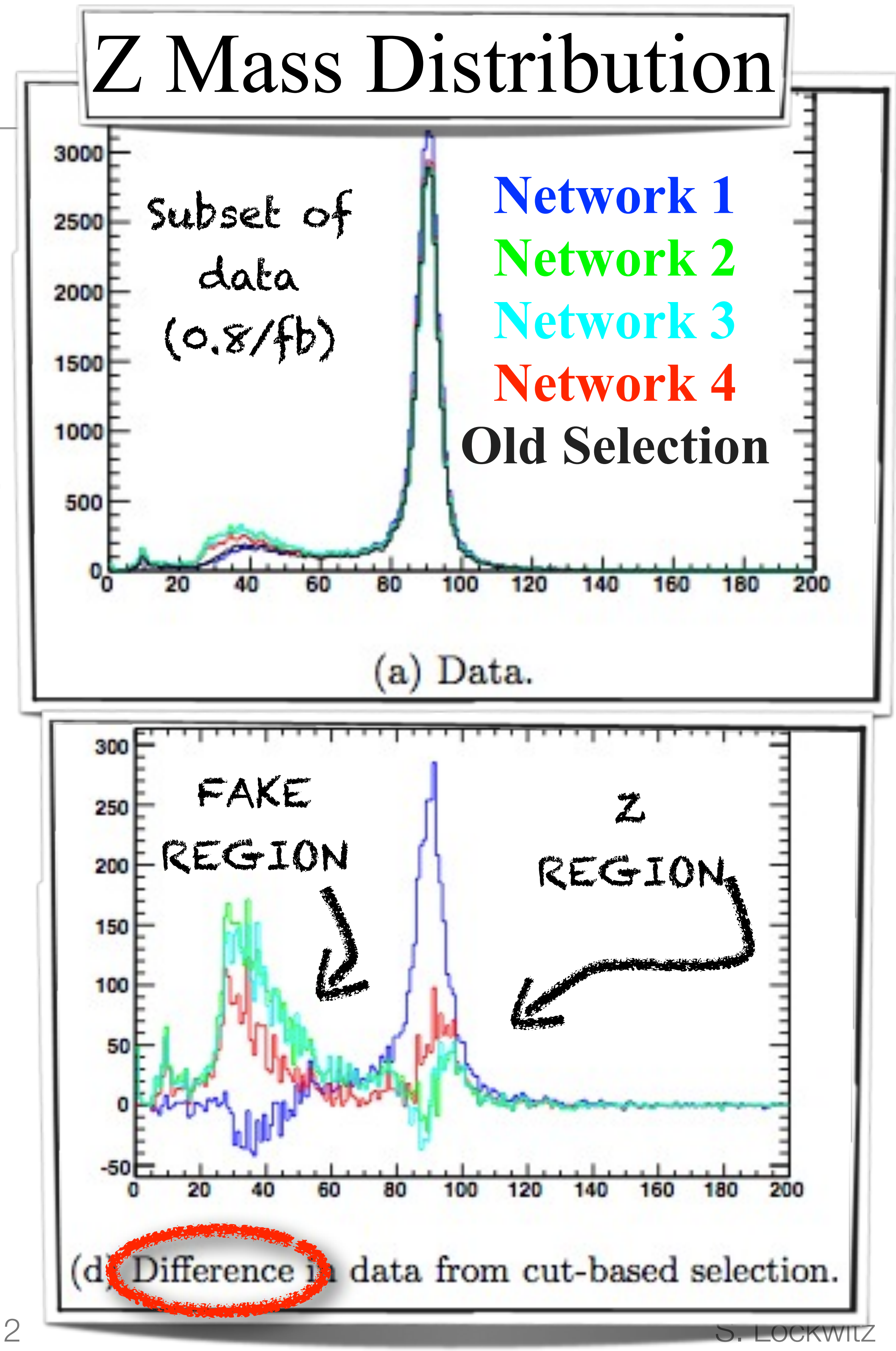
Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value
- Score values were selected by evaluating the Z mass distribution in a subset of MC & data & looking at the **change** from the old selection
- Looked for improvement in Z w/o increasing "fakes"



Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value
- Score values were selected by evaluating the Z mass distribution in a subset of MC & data & looking at the **change** from the old selection
- Looked for improvement in Z w/o increasing "fakes"
- Central pairs have an opposite charge req.
- $76 \leq M_{ee} \leq 106$ GeV/c^2



Improvement?

Improvement?

- What exactly are we adding?

Improvement?

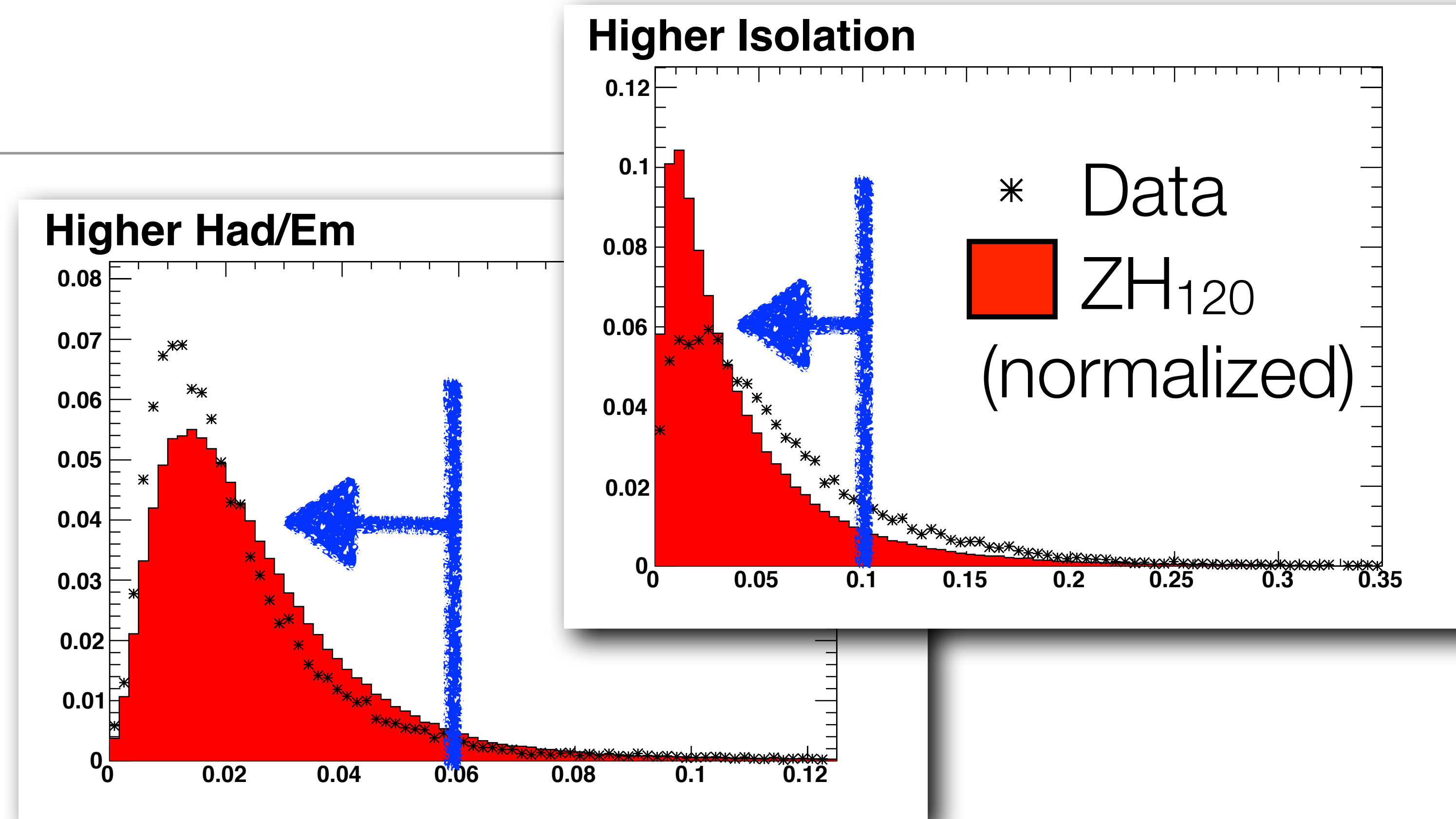
- What exactly are we adding?
- As an example, traditional cut-based selection has isolation and Had./EM requirements of
  - $Isol/E_T \leq 0.1$
  - $Had/EM \lesssim 0.06$

Improvement?

- What exactly are we adding?
- As an example, traditional cut-based selection has isolation and Had./EM requirements of
  - $Isol/E_T \leq 0.1$
  - $Had/EM \lesssim 0.06$
- The network selection allows for

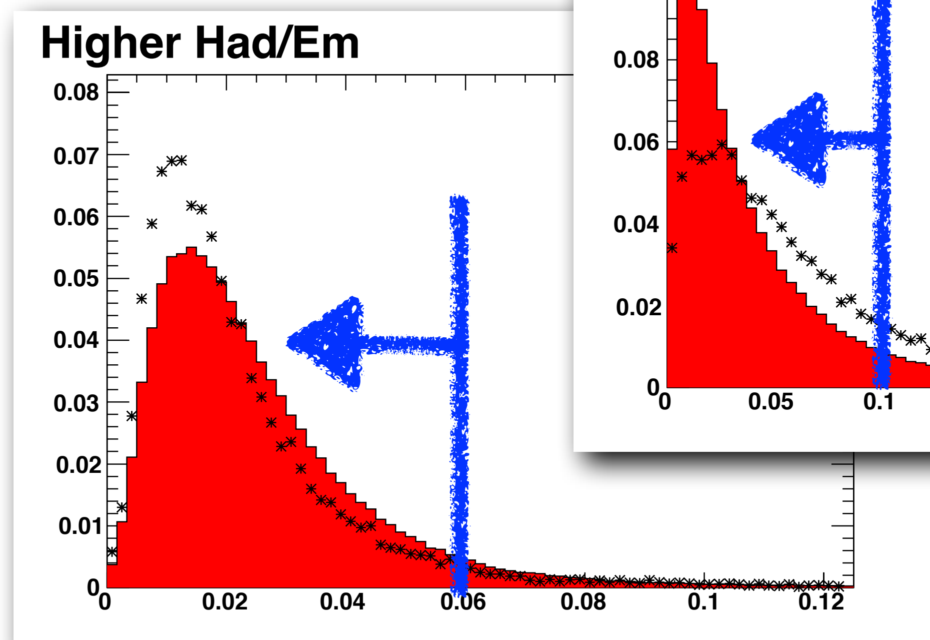
Improvement?

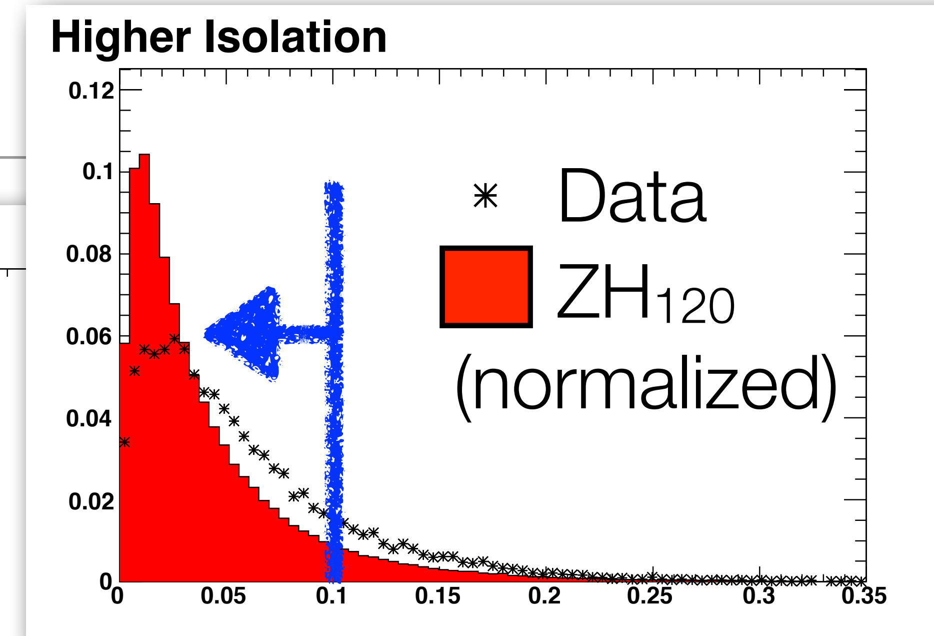
- What exactly are we adding?
- As an example, traditional cut-based selection has isolation and Had./EM requirements of
  - $Isol/E_T \leq 0.1$
  - $Had/EM \lesssim 0.06$
- The network selection allows for

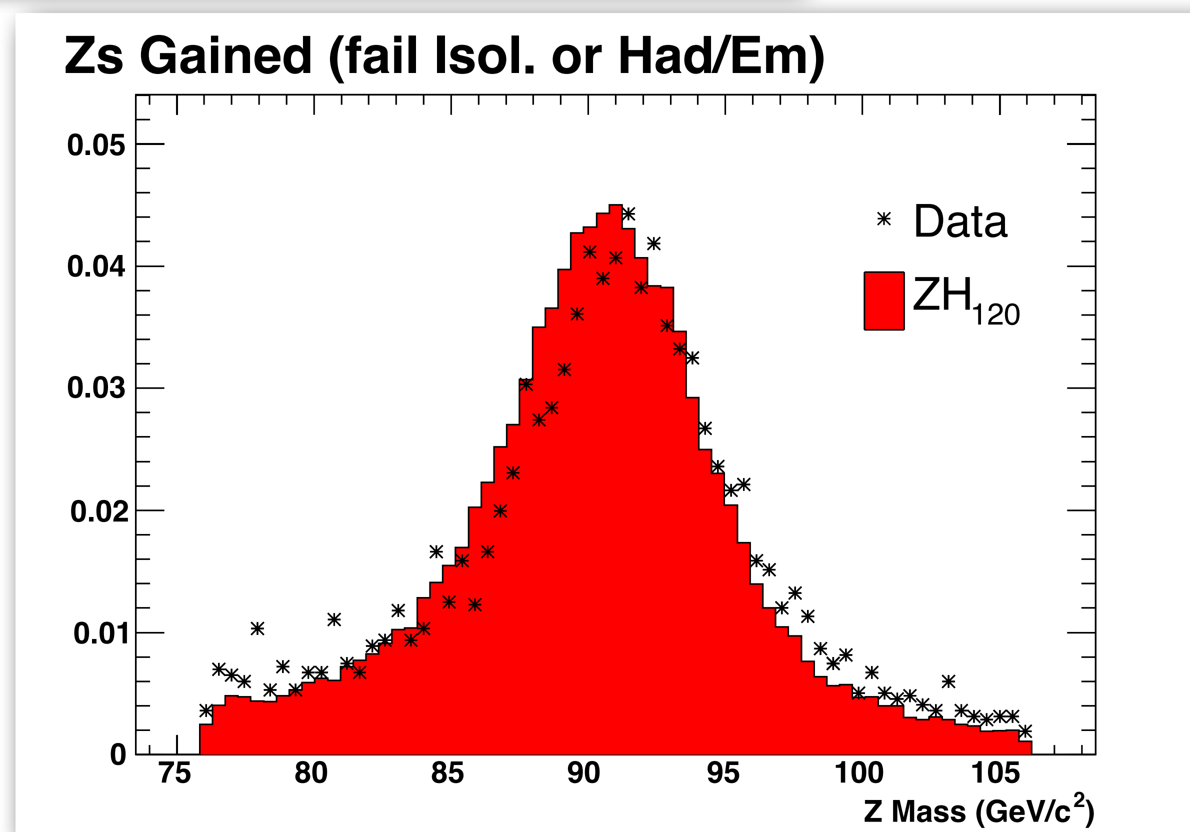


Improvement?

- What exactly are we adding?
- As an example, traditional cut-based selection has isolation and Had./EM requirements of
  - Isol/$E_T \leq 0.1$
  - Had/EM $\lesssim 0.06$
- The network selection allows for
- Are these terrible?







Improvement

Improvement

- Trigger + Electron ID led to a ~8% increase in acceptance for data and ZH signal (events with $76 \leq m_Z \leq 106$ GeV/c^2, two jets)

Improvement

- Trigger + Electron ID led to a ~8% increase in acceptance for data and ZH signal (events with $76 \leq m_Z \leq 106$ GeV/c^2, two jets)

  - This is great! It's like 0.6/fb more data, or having the Tevatron run for ~3 more months

- Technicalities resulting in losses:
  - An over-aggressive requirement on "crack-track" Z's led to a reduction in acceptance (1-2%)

Improvement

- Trigger + Electron ID led to a ~8% increase in acceptance for data and ZH signal (events with $76 \leq m_Z \leq 106$ GeV/c^2, two jets)

  - This is great! It's like 0.6/fb more data, or having the Tevatron run for ~3 more months

- Technicalities resulting in losses:
  - An over-aggressive requirement on "crack-track" Z's led to a reduction in acceptance (1-2%)
  - A loose forward cut-based selection was considered, but ultimately omitted (~1%)

Improvement

- Trigger + Electron ID led to a ~8% increase in acceptance for data and ZH signal (events with $76 \leq m_Z \leq 106$ GeV/c^2, two jets)

- This is great! It's like 0.6/fb more data, or having the Tevatron run for ~3 more months

- Technicalities resulting in losses:
  - An over-aggressive requirement on "crack-track" Z's led to a reduction in acceptance (1-2%)
  - A loose forward cut-based selection was considered, but ultimately omitted (~1%)
- Overall, cleaner selection (segue to next slide)!

Modeling Misidentified Electrons

Modeling Misidentified Electrons

- To find the rate at which a jet will mimic the electron signature, we

Modeling Misidentified Electrons

- To find the rate at which a jet will mimic the electron signature, we
  - Run over jet-triggered data samples (20, 50, 70, 100)

Modeling Misidentified Electrons

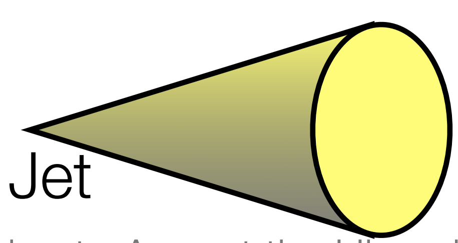
- To find the rate at which a jet will mimic the electron signature, we
  - Run over jet-triggered data samples (20, 50, 70, 100)
  - Apply a W & Z veto on events (MET<15 and only one possible electron)

Modeling Misidentified Electrons

- To find the rate at which a jet will mimic the electron signature, we
  - Run over jet-triggered data samples (20, 50, 70, 100)
  - Apply a W & Z veto on events (MET<15 and only one possible electron)
  - Throw out the lead p_T jet in an attempt to remove trigger bias

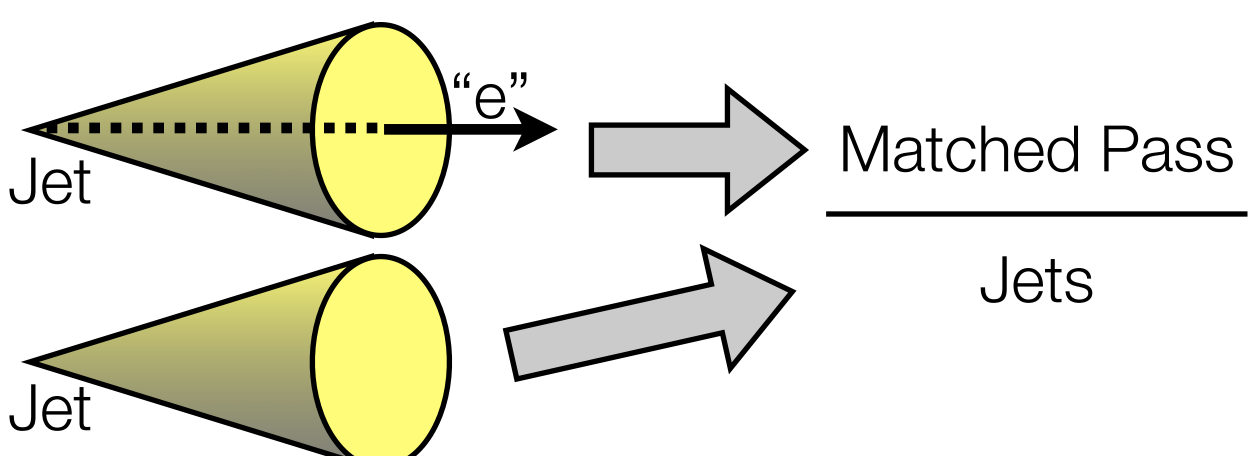
Modeling Misidentified Electrons

- To find the rate at which a jet will mimic the electron signature, we
  - Run over jet-triggered data samples (20, 50, 70, 100)
  - Apply a W & Z veto on events (MET<15 and only one possible electron)
  - Throw out the lead p_T jet in an attempt to remove trigger bias
  - remaining jets enter as denominator objects



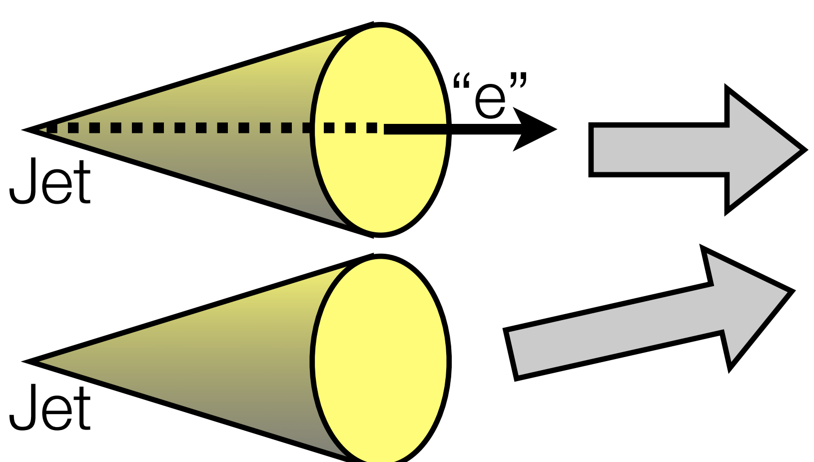
Modeling Misidentified Electrons

- To find the rate at which a jet will mimic the electron signature, we
  - Run over jet-triggered data samples (20, 50, 70, 100)
  - Apply a W & Z veto on events (MET<15 and only one possible electron)
  - Throw out the lead p_T jet in an attempt to remove trigger bias
  - remaining jets enter as denominator objects
  - if a denominator jet has an electron passing selection within a cone of 0.4, it enters as a numerator object

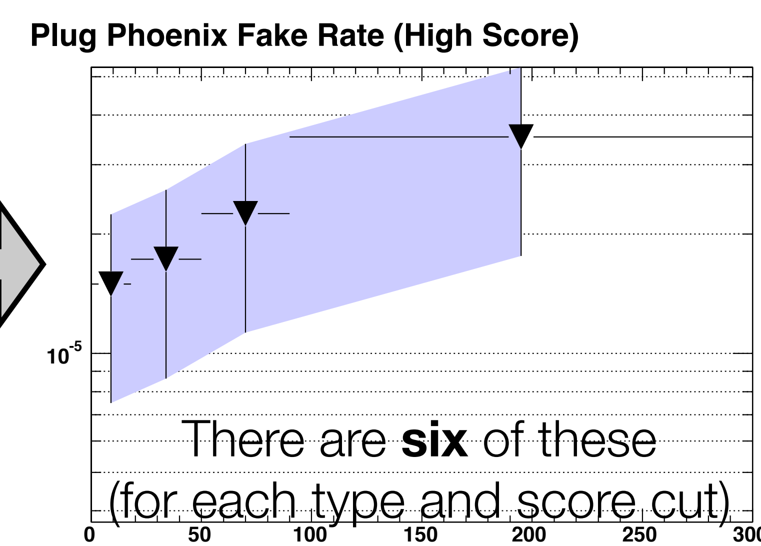


Modeling Misidentified Electrons

- To find the rate at which a jet will mimic the electron signature, we
  - Run over jet-triggered data samples (20, 50, 70, 100)
  - Apply a W & Z veto on events (MET<15 and only one possible electron)
  - Throw out the lead p_T jet in an attempt to remove trigger bias
  - remaining jets enter as denominator objects
  - if a denominator jet has an electron passing selection within a cone of 0.4, it enters as a numerator object
  - this ratio is found in bins of E_T for each jet-triggered sample. The average is used and a 50% uncertainty is applied to cover the difference in rates



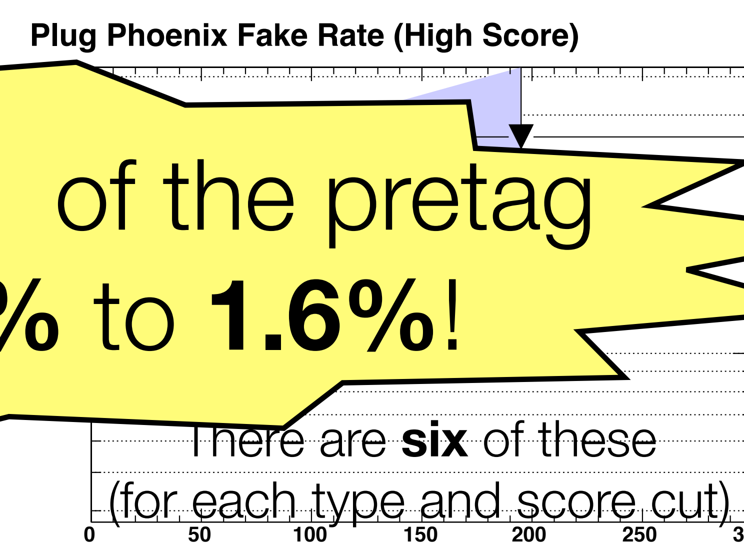
$$\frac{\text{Matched Pass}}{\text{Jets}} = \text{Rate}$$



Modeling Misidentified Electrons

- To find the rate at which a jet will mimic the electron signature, we
  - Run over jet-triggered data samples (20, 50, 70, 100)
  - Apply a W & Z veto on events (MET<15 and only one possible electron)
  - Throw out the lead p_T jet in an attempt to remove trigger bias
  - remaining jets enter as denominator objects
  - if a denominator jet has an electron passing selection within a cone of 0.4, it enters as a numerator object
  - this ratio is found in bins of E_T for each jet-triggered sample. The average is used and a 50% uncertainty is applied to cover the difference in rates

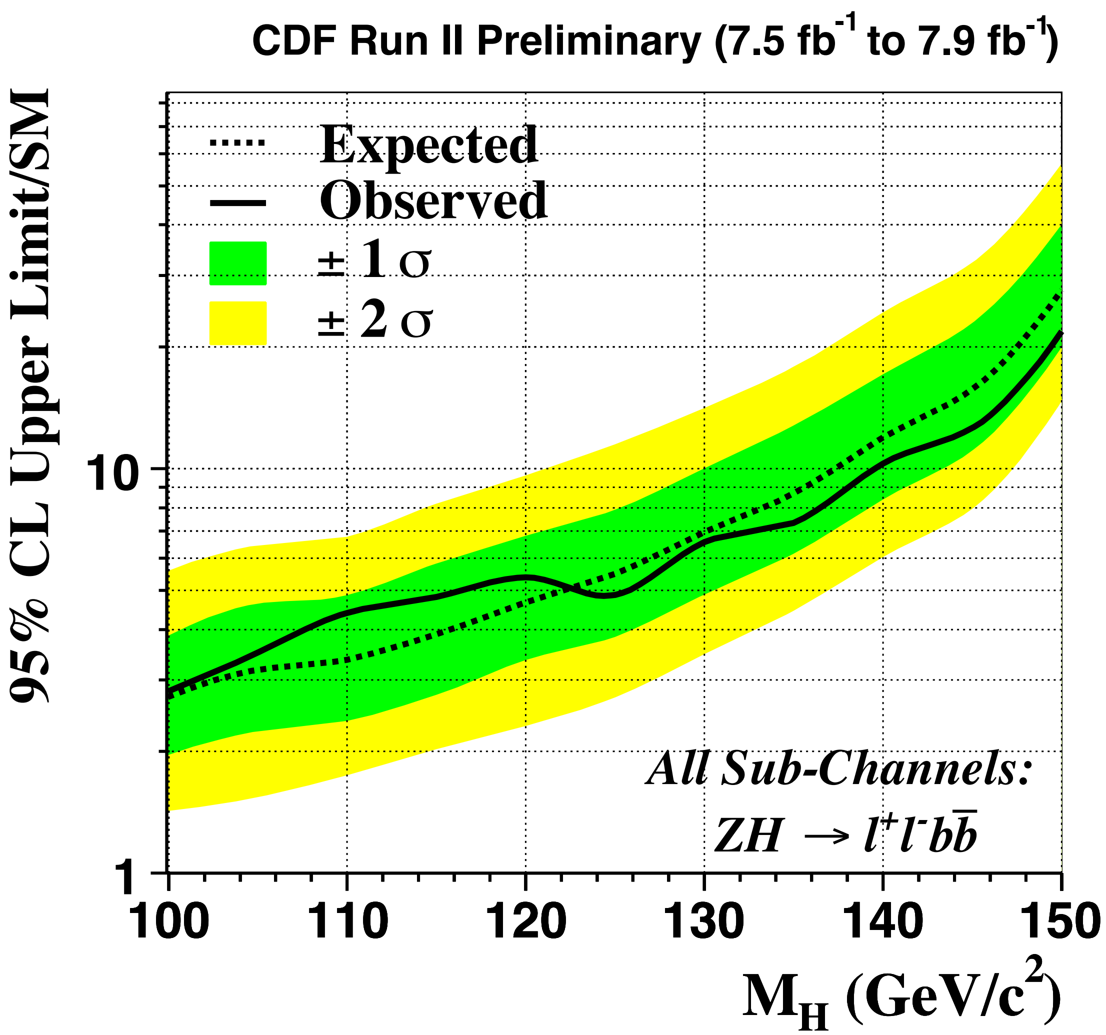
The resulting "fake" contribution of the pretag sample was reduced from **8%** to **1.6%**!



Back to the Big Picture

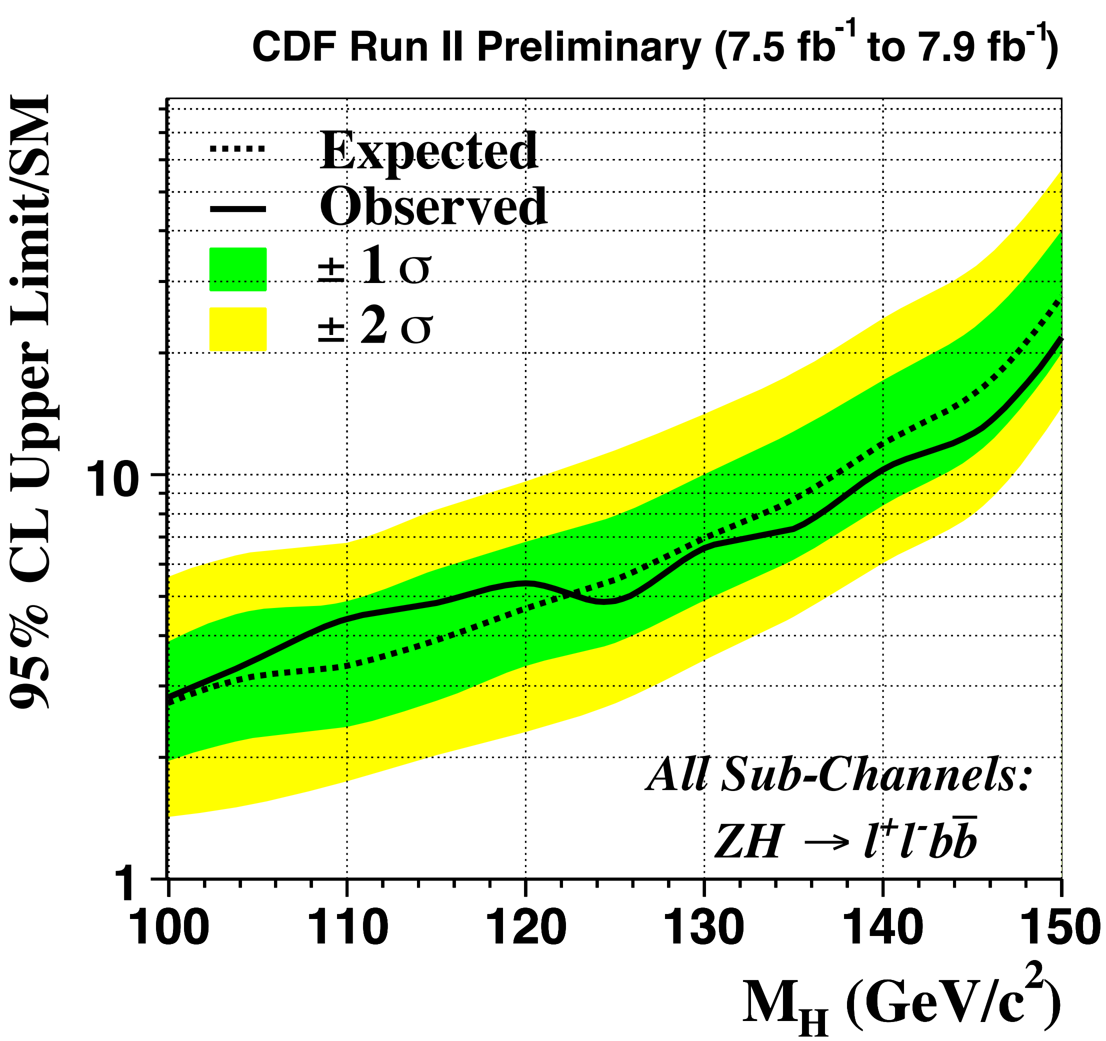
Back to the Big Picture

- This analysis was combined with the ZH to μμbb analysis



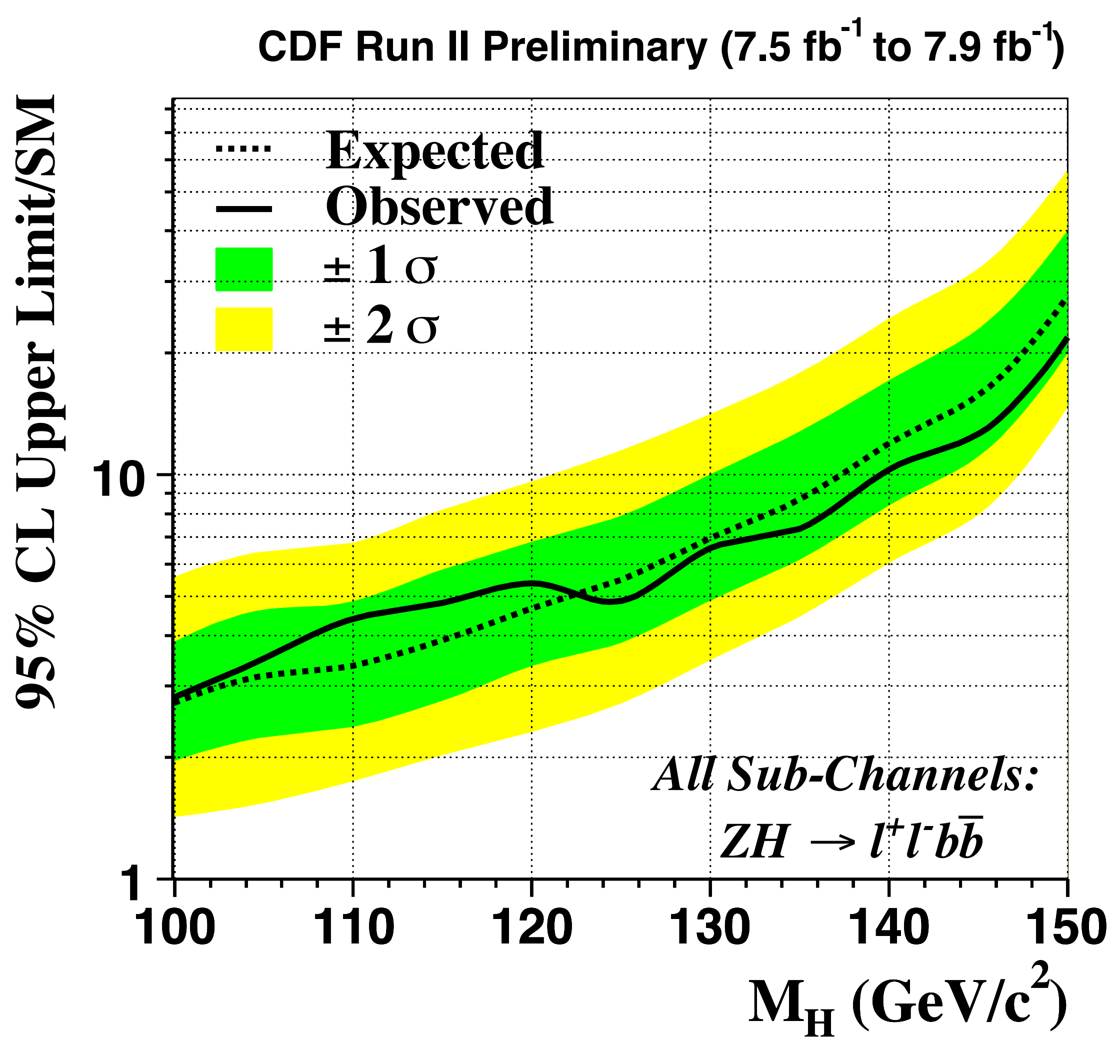
Back to the Big Picture

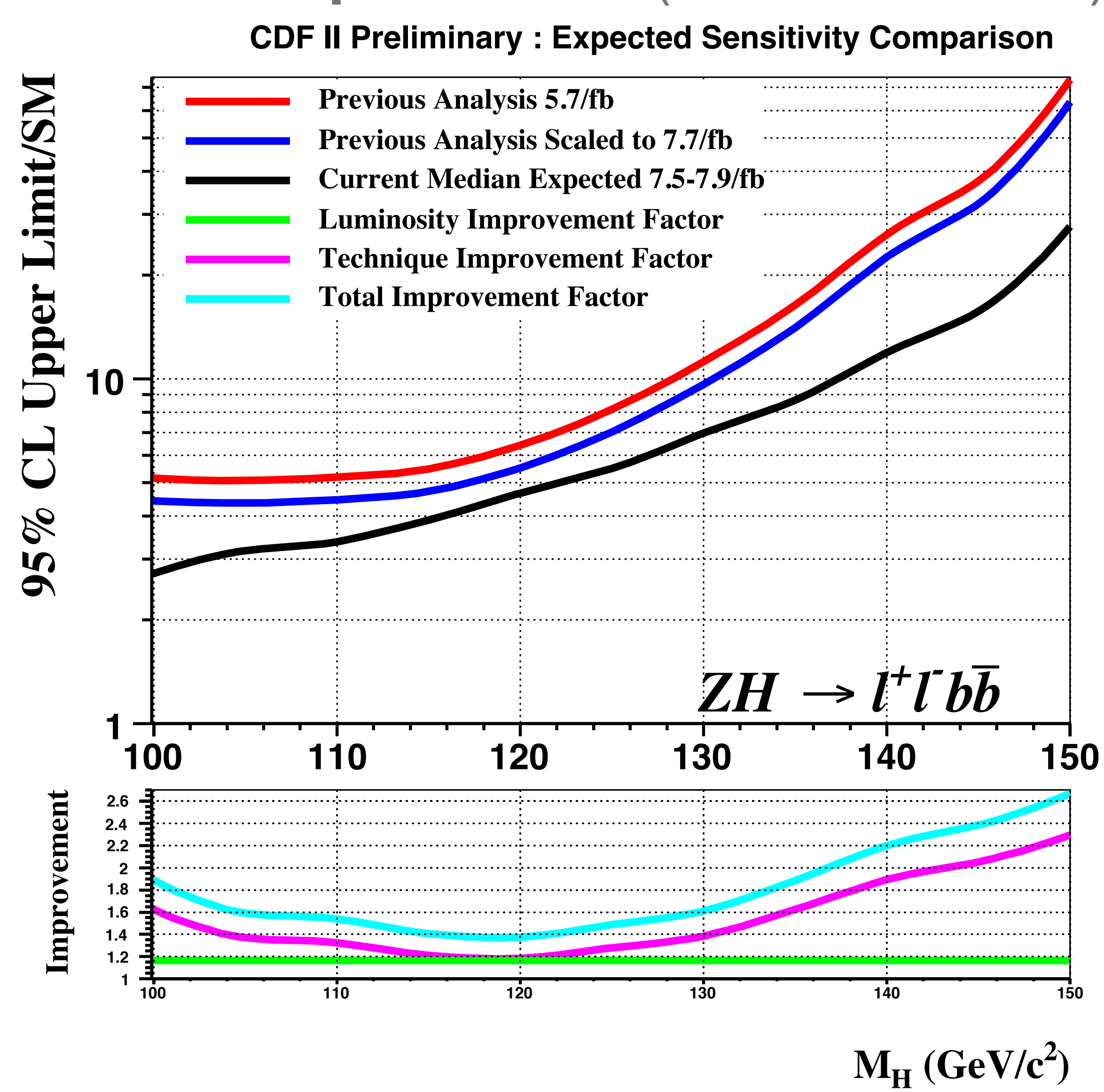
- This analysis was combined with the ZH to μμbb analysis
  - Limit plot: 95% CL upper limits on the Higgs boson production cross section as a function of the Higgs boson mass, divided by the expected SM Higgs boson cross section ($\sigma_{ZH(llbb)}/\sigma_{SM(ZHllbb)}$); values <1 are considered excluded



Back to the Big Picture

- This analysis was combined with the ZH to μμbb analysis
  - Limit plot: 95% CL upper limits on the Higgs boson production cross section as a function of the Higgs boson mass, divided by the expected SM Higgs boson cross section ($\sigma_{ZH(llbb)}/\sigma_{SM(ZHllbb)}$); values <1 are considered excluded
- Many improvements in both analyses led to a **~20% improvement** (m_H=120 GeV/c^2) in sensitivity due to technique alone

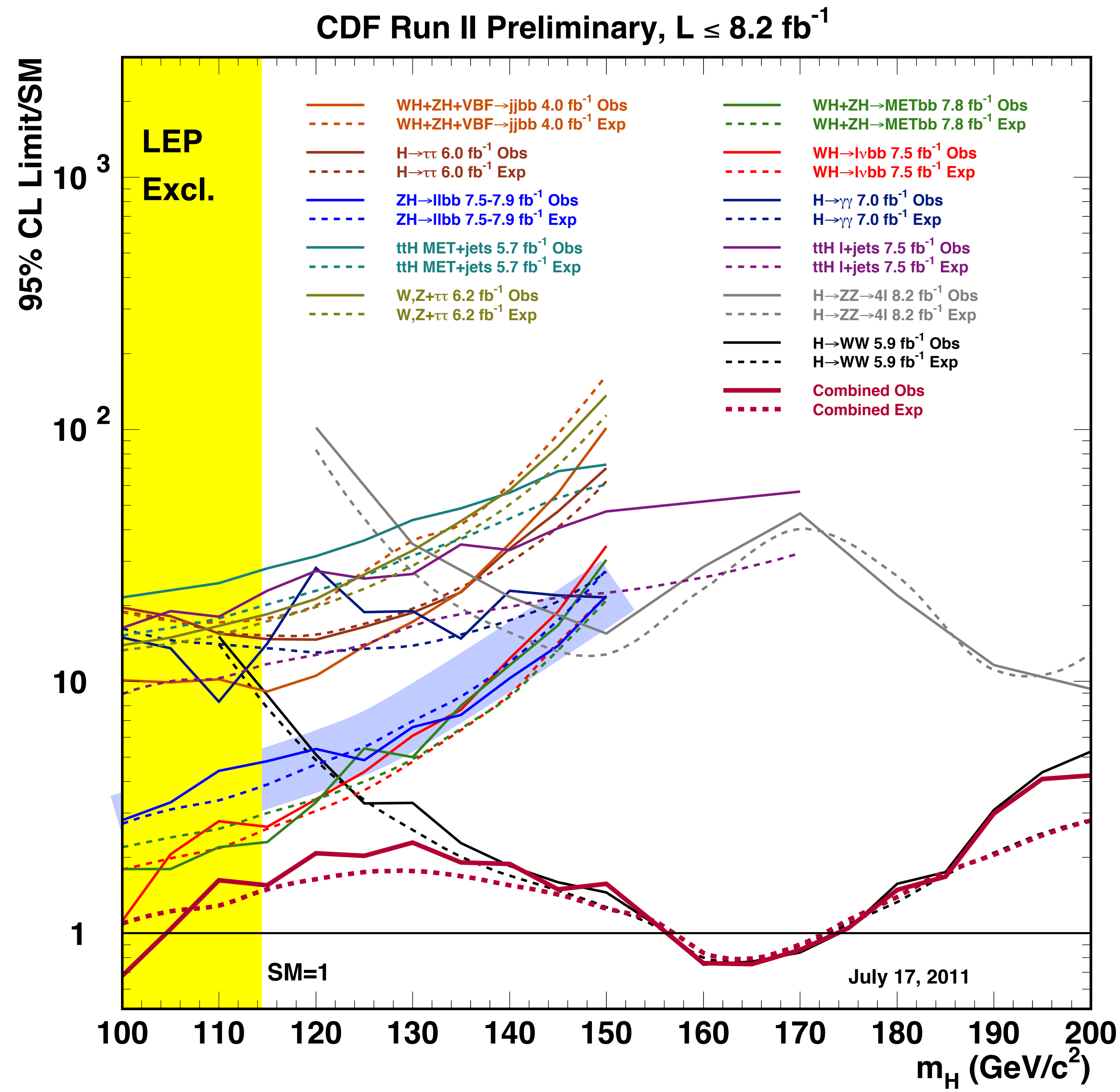




Bigger Picture: ZH to llbb in Perspective

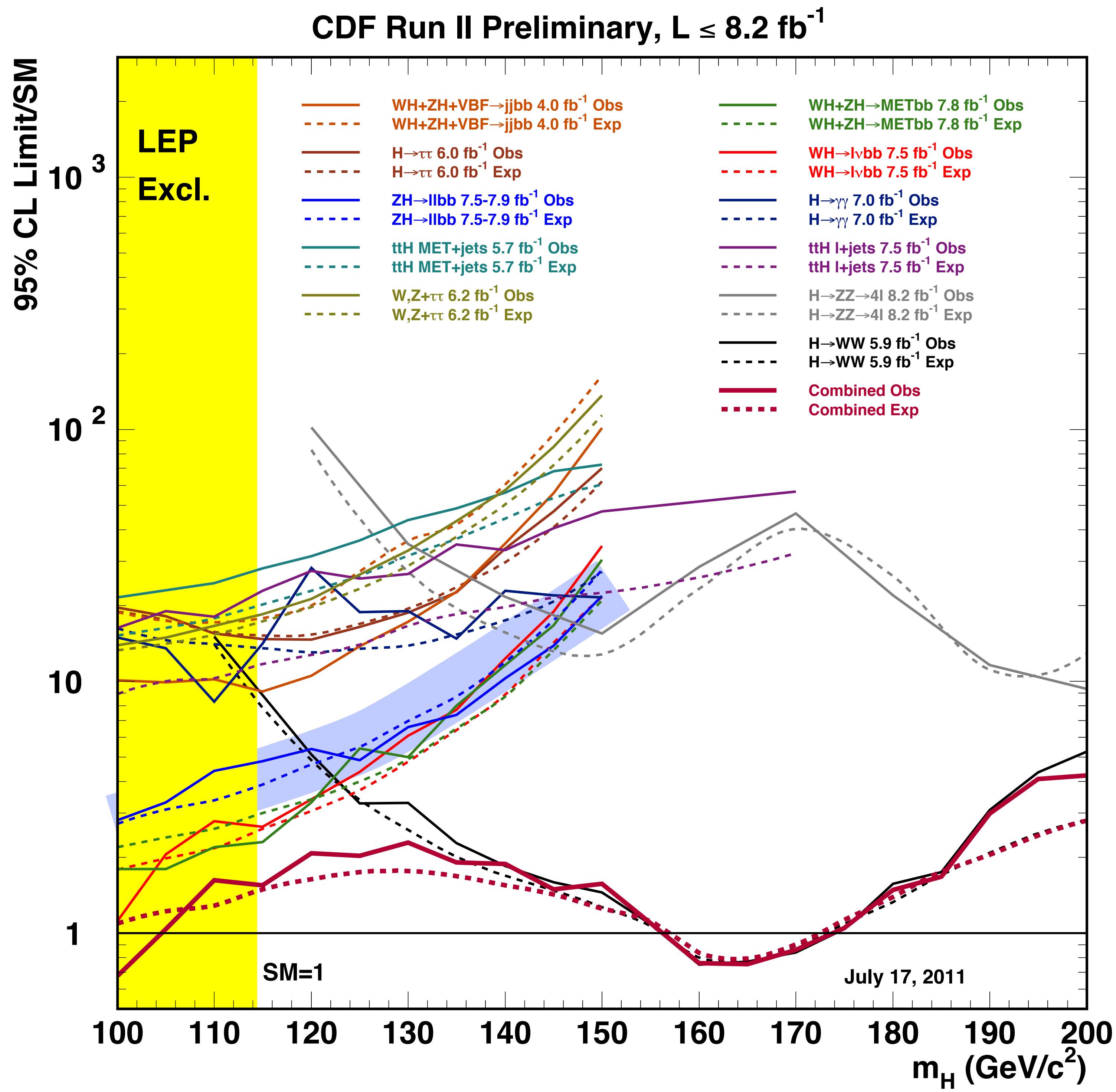
Bigger Picture: ZH to llbb in Perspective

- One of the main contributors at low mass



Bigger Picture: ZH to llbb in Perspective

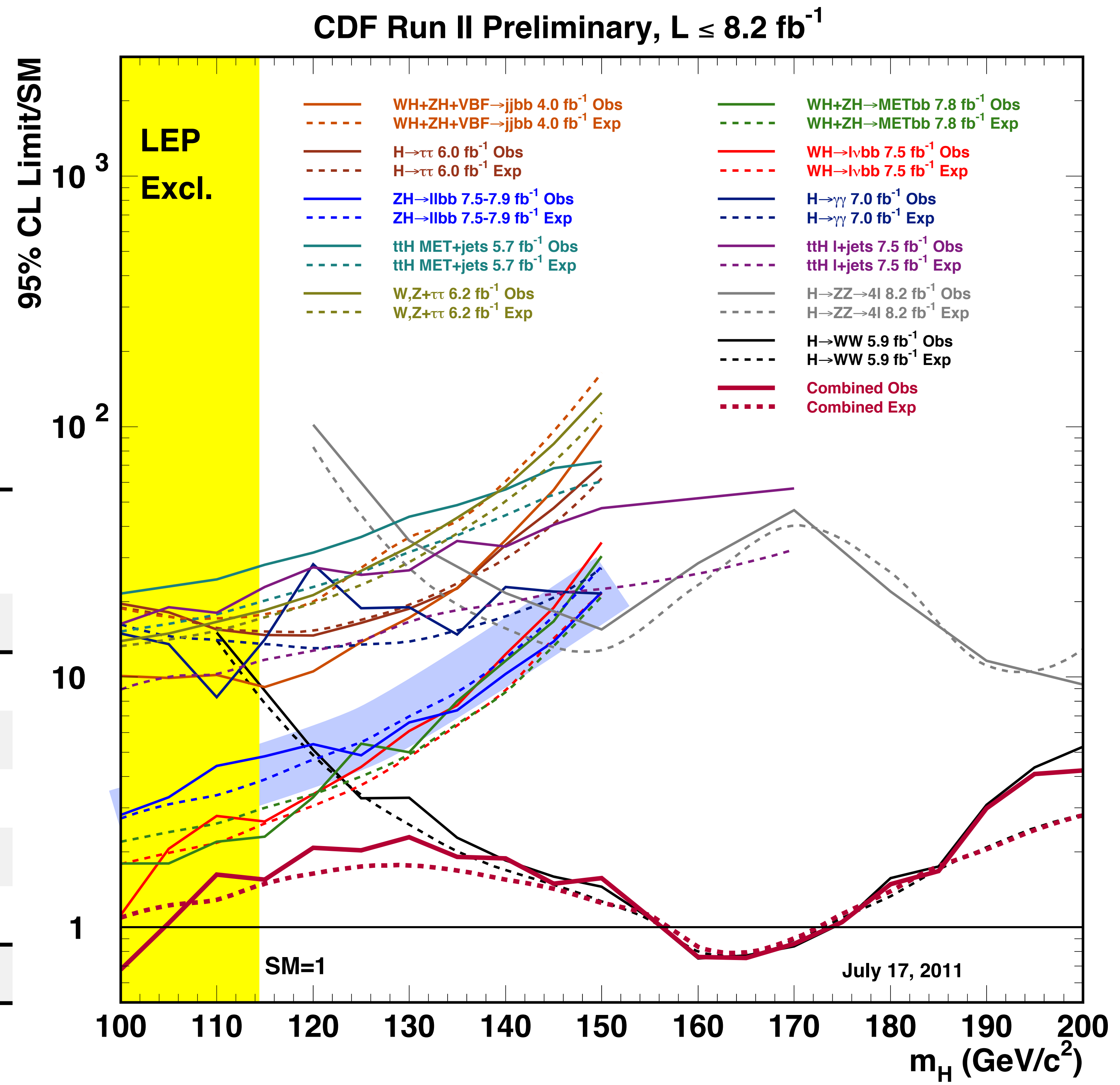
- One of the main contributors at low mass
- Improvement here greatly helps the Tevatron result



Bigger Picture: ZH to llbb in Perspective

- One of the main contributors at low mass
- Improvement here greatly helps the Tevatron result

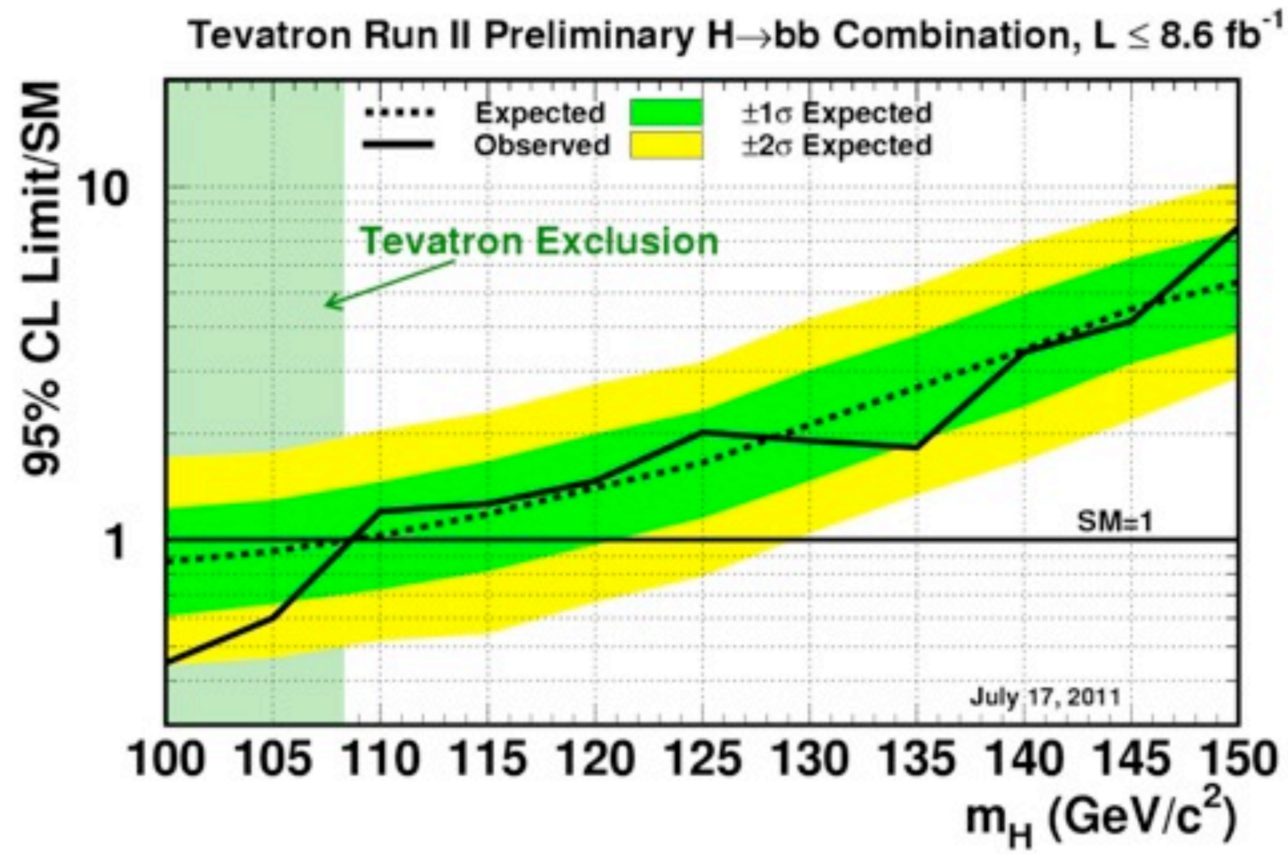
	Expected Limit (σ/σ_{SM}) at 120 GeV/c^2	
	CDF	D0
WH	3.06	4.3
ZH/WH to ννbb	3.36	4.5
ZH to llbb	***4.67***	***5.5***
H to WW	4.86	5.46
H to ττ	13.9	14.2
Combination	1.24	



Bigger Picture: ZH to llbb in Perspective

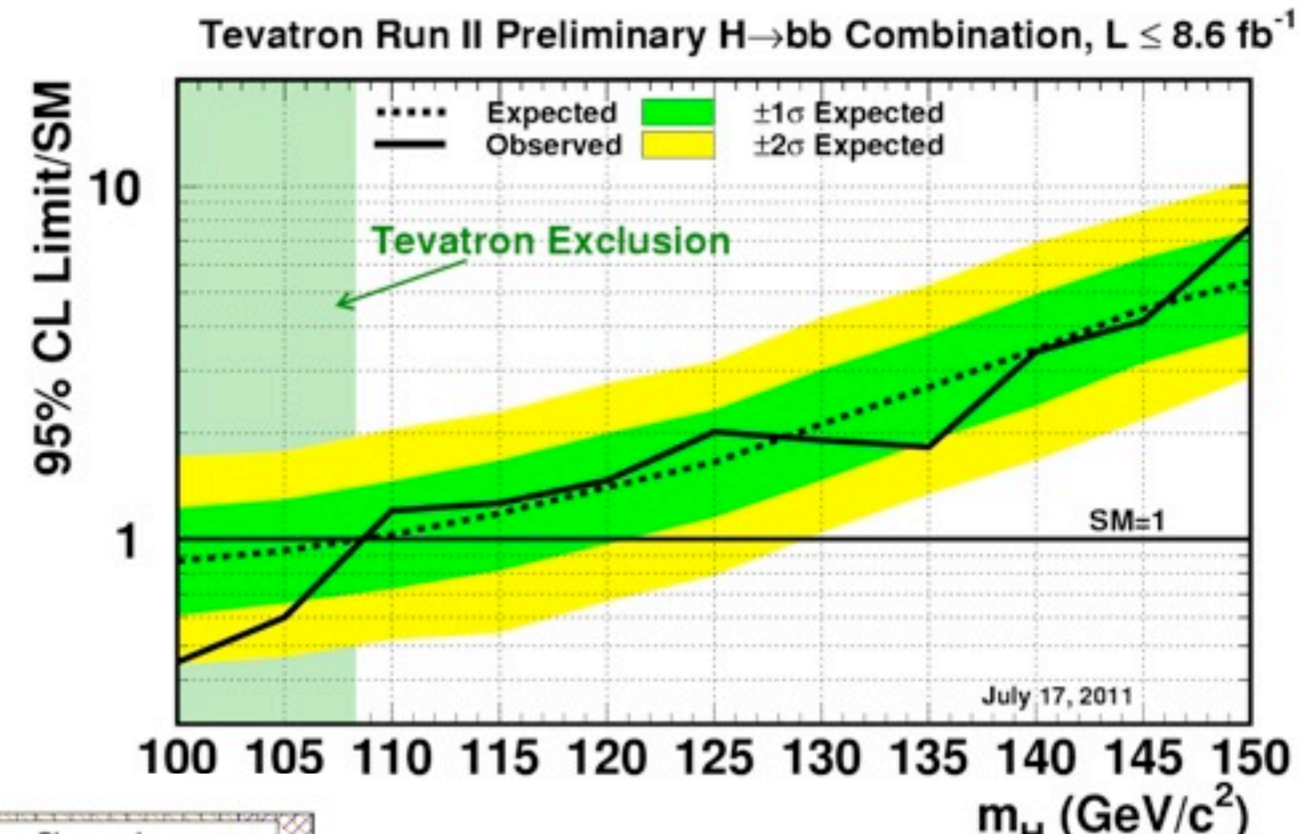
Bigger Picture: ZH to llbb in Perspective

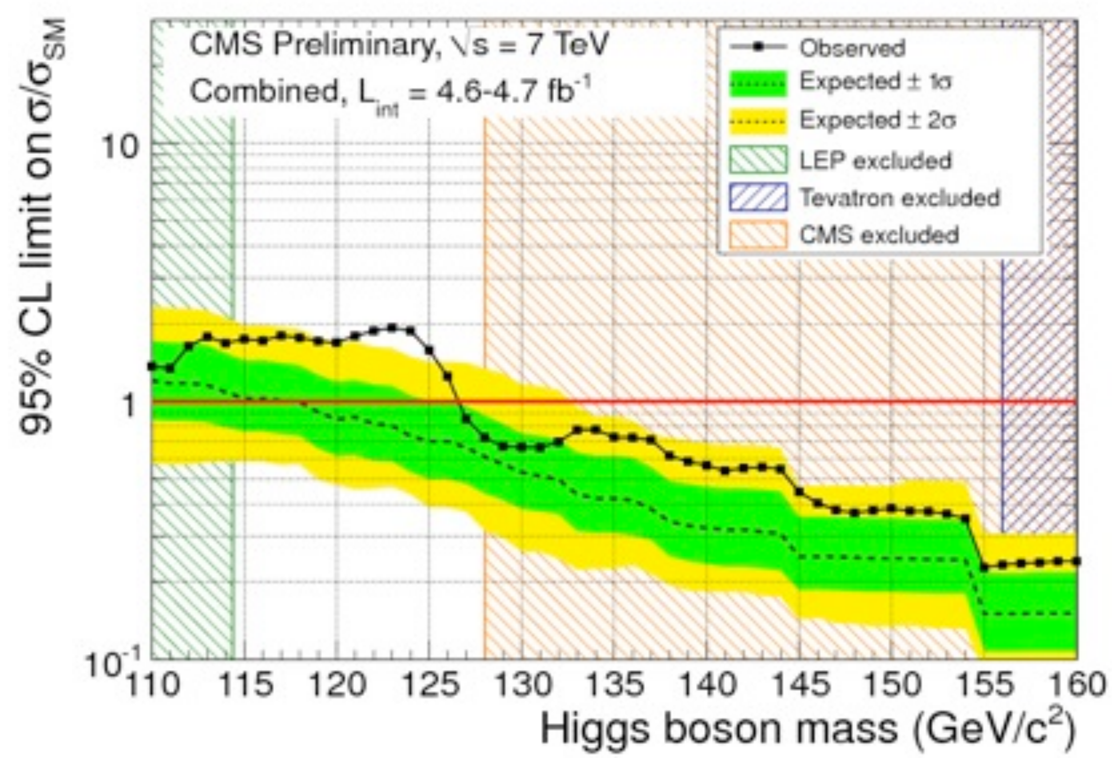
- Measurement here is also important in the case of **observance**
  - H to bb allows for a m_H measurement at the Tevatron

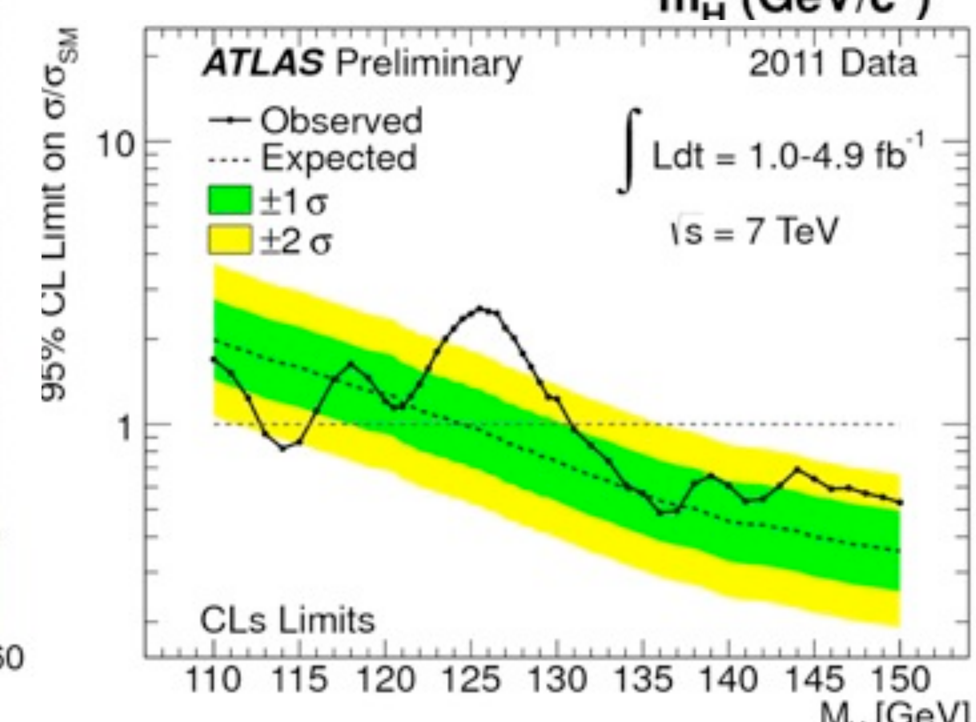


Bigger Picture: ZH to llbb in Perspective

- Measurement here is also important in the case of **observance**
  - H to bb allows for a m_H measurement at the Tevatron
- LHC is beginning to see very interesting results

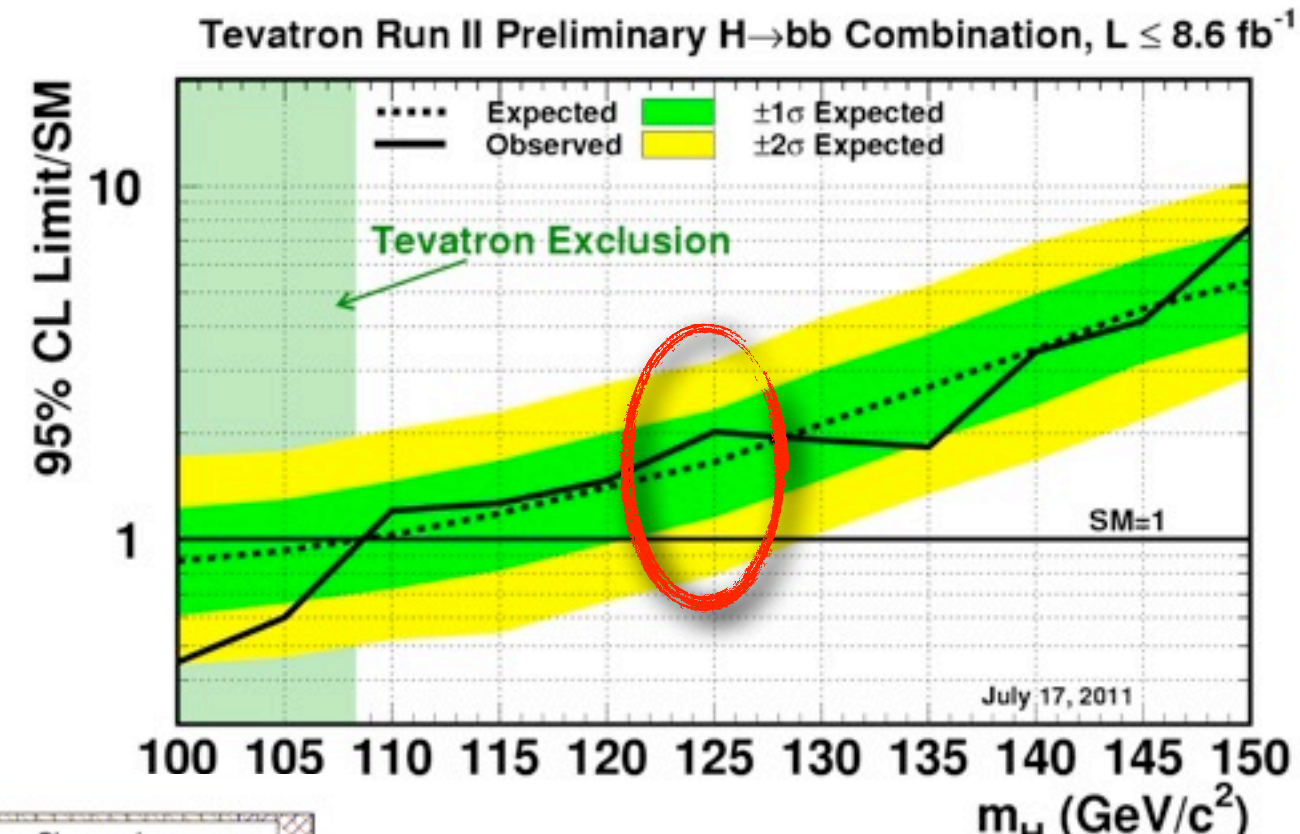


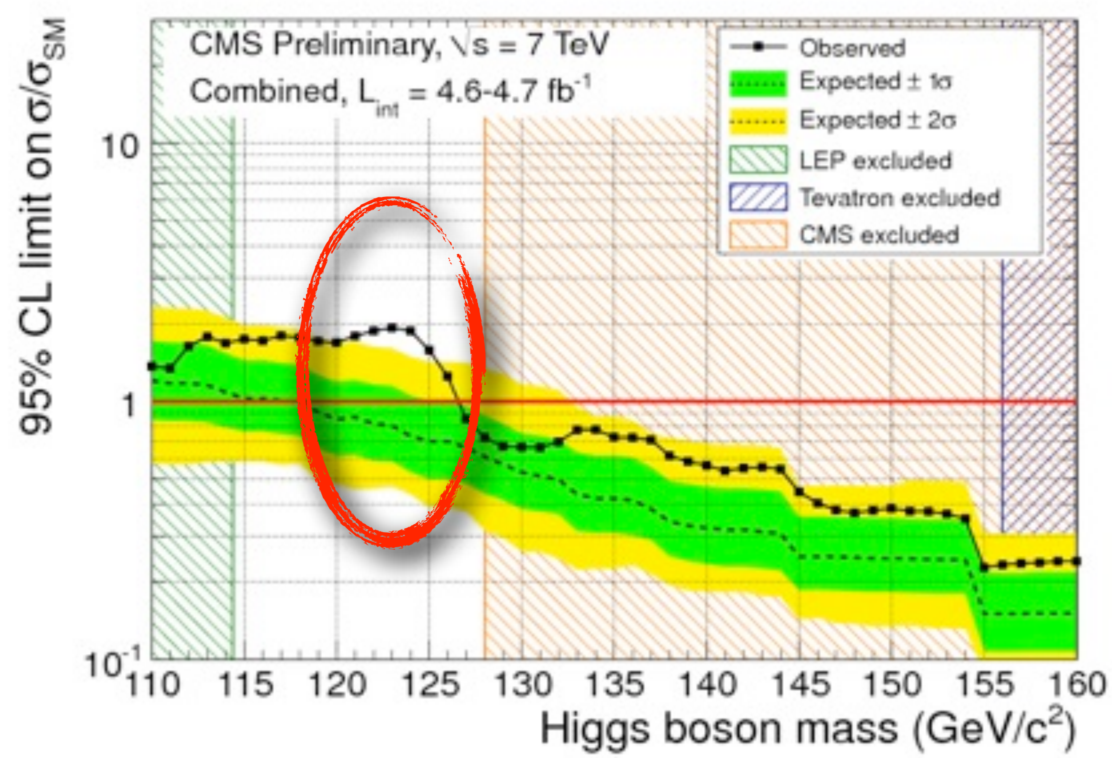


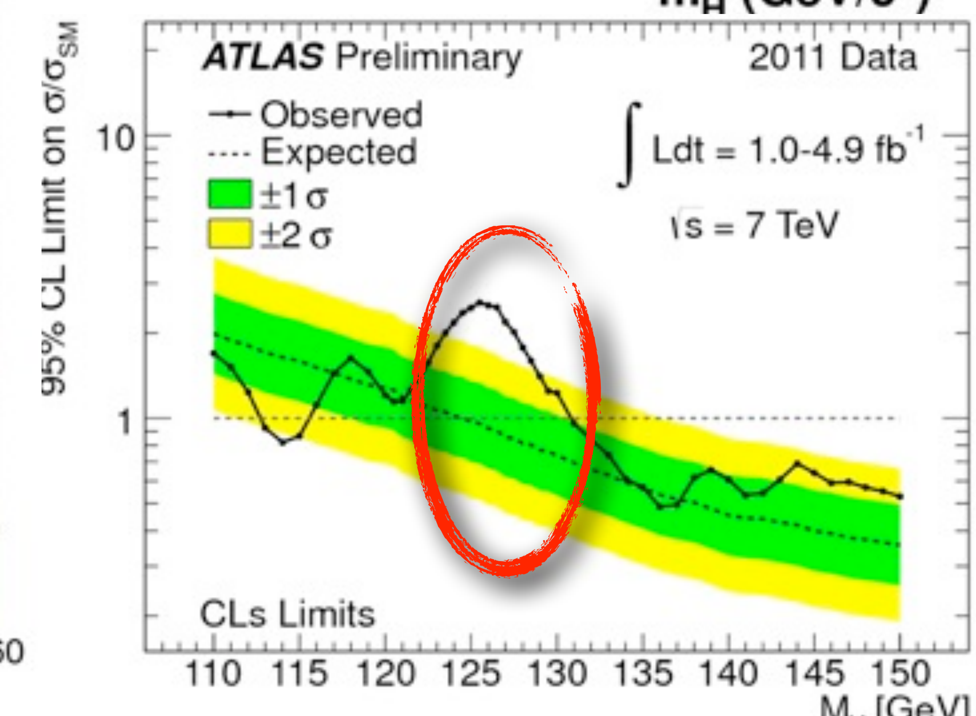


Bigger Picture: ZH to llbb in Perspective

- Measurement here is also important in the case of **observance**
  - H to bb allows for a m_H measurement at the Tevatron
- LHC is beginning to see very interesting results
- If they see something, we should likely see something soon as well!

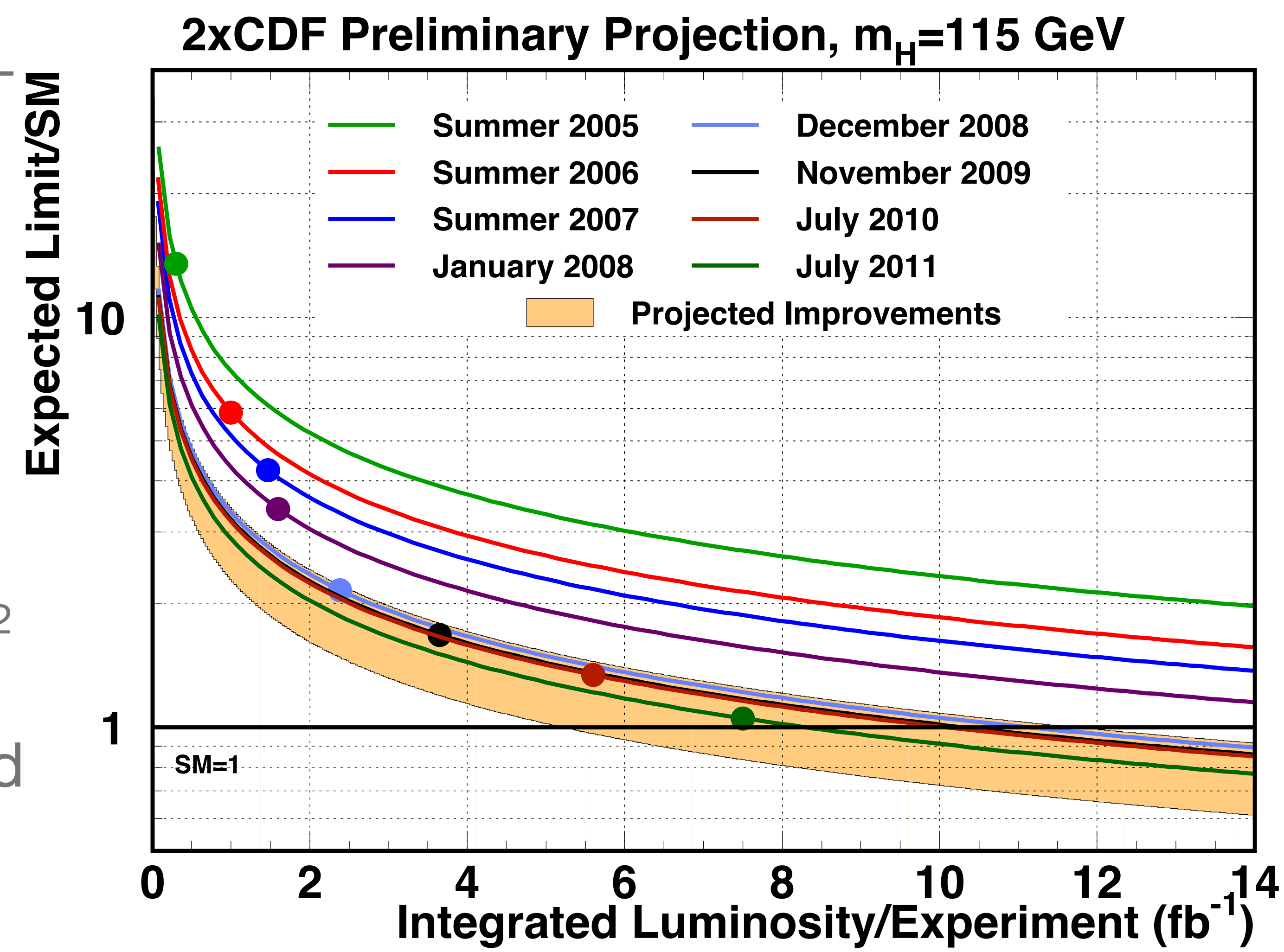






Outlook

- TeV plan of Moriond with ~10/fb
- Exciting improvements in b tagging + new data
- LHC is seeing exciting hints in the data -- Tev provides a complementary approach
  - In any case, the world will ask what we see $115 \leq m_H \leq 140$ GeV/c^2
  - With the full dataset, our expected sensitivity at m_H=125 GeV/c^2 is 2.6 sigma exclusion
- **Very interesting 2012!**

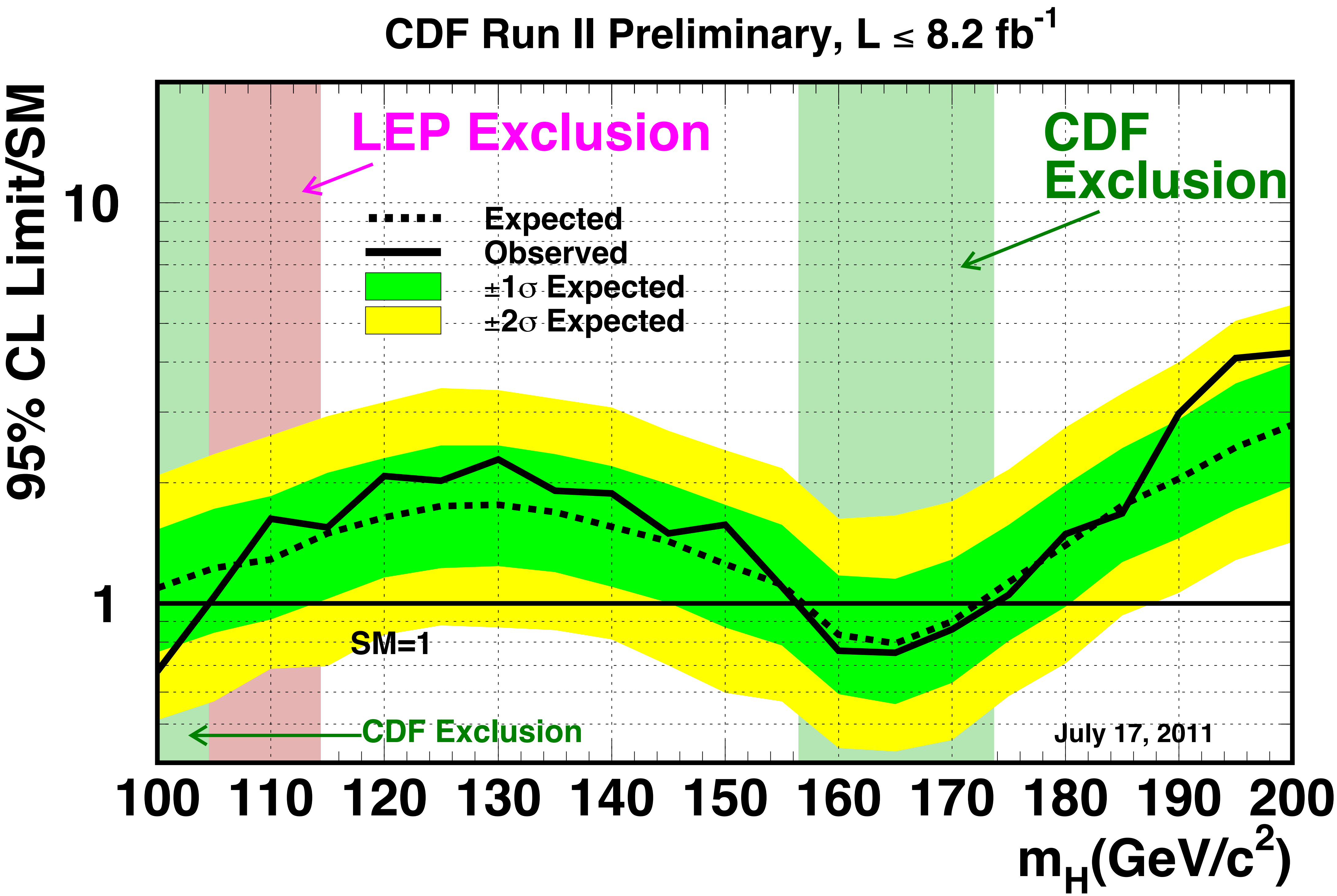


Back-up Slides

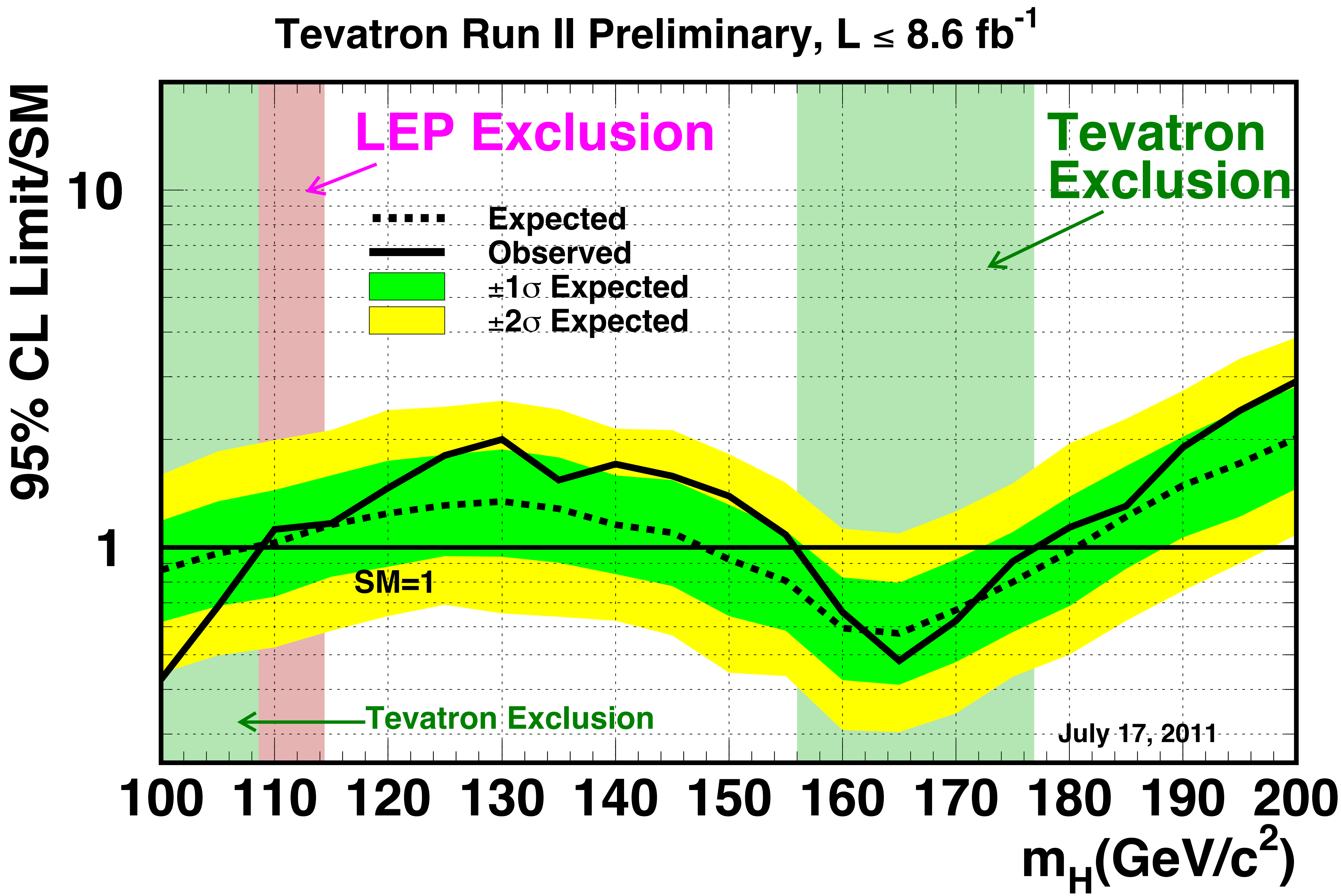
Variable Definitions

- Track P_T: Transverse momentum of track
- Isolation Ratio: Total isolation over EmE_T
- Had/Em: Hadronic energy of cluster over electromagnetic energy of cluster
- Track Isolation: Sum the P_T of tracks ($R<=0.4$ and $\Delta Z<5$ cm) minus the seed track P_T (non-ratio).
- Total Cal. Isolation (R=0.4): Isolation in both EM and Had calorimeters (not a ratio).
- E/P: Ratio of transverse energy to transverse momentum
- Energy: Energy of the electron 4-vector
- Silicon Hits: Total number of silicon hits associated with the track
- PesPem ΔR: $\sqrt{(\eta_{Pem} - \eta_{Pes})^2+(\phi_{Pem} - \phi_{Pes})^2}$
- Pes 2d 5x9 U(V): Energy in central 5 strips of the PES over the energy of the cluster's 9 strips in the U (or V) plane
- Had Isol (R=0.4): Excess hadronic transverse energy in a cone of 0.4 of the center of the cluster (non-ratio)
- Pes 2d Energy: Energy cluster deposited in the U layer
- Pem 3x3 χ^2: "A quantitative assessment of the pattern of EM energy deposition for a given cluster, relative to testbeam." (cdf5975)
- Em E_T: Transverse energy of cluster in the electromagnetic calorimeter
- Plug Preradiator Energy: Energy deposited in towers associated with the cluster in the first scintillating layer of the PEM
- Had E_T: Transverse energy of cluster in hadronic calorimeter

CDF and Tevatron Combinations



CDF and Tevatron Combinations



Efficiencies

Tag-and-probe efficiencies: (probe leg passes trigger preselection)

	High Score	Low Score
Central ϵ_{data}	0.942 ± 0.004	0.978 ± 0.004
Central ϵ_{MC}	0.940 ± 0.002	0.978 ± 0.002
Scale Factor	1.002 ± 0.005	1.000 ± 0.005
Forward Phoenix ϵ_{data}	0.891 ± 0.004	0.956 ± 0.005
Forward Phoenix ϵ_{MC}	0.917 ± 0.003	0.973 ± 0.003
Scale Factor	0.972 ± 0.006	0.983 ± 0.006
Forward Non-Phoenix ϵ_{data}	0.540 ± 0.005	0.658 ± 0.005
Forward Non-Phoenix ϵ_{MC}	0.812 ± 0.004	0.890 ± 0.005
Scale Factor	0.664 ± 0.007	0.739 ± 0.007

Table 4.13: The alternate method of finding efficiencies. These are currently not applied in the analysis, but are meant to serve as a scale for the identification efficiency.

<u>ZH event Z efficiency:</u>

-67.5% (for events generated ZH to eebb)
-74.7% (subset w/ two electron candidates clustered in ntuple)
-96.4% (subset w/ two candidates that pass trigger preselection)

Biggest loss here was due to:
- forward $|\eta|$ or Phoenix requirements
- Had/Em
- track z_0

Why Trigger Score is a Probability

$$
\begin{aligned}
\text{Error} &= \frac{1}{2}\sum_{i}^{\#Fired}(f(x_i)-1)^2+\frac{1}{2}\sum_{j}^{\#NotFired}(f(x_j)-0)^2 \\
\frac{\partial\text{Error}}{\partial f(x)}=0 &= \sum_{i}^{\#Fired}(f(x_i)-1)+\sum_{j}^{\#NotFired}f(x_j) \\
0 &= -(\#Fired)+\sum_{i}^{\#Fired}f(x_i)+\sum_{j}^{\#NotFired}f(x_j) \\
(\#Fired) &= \sum_{i}^{\#Fired}f(x_i)+\sum_{j}^{\#NotFired}f(x_j)
\end{aligned}
$$

Now, if the error on f(x) is minimized perfectly, we can evaluate this relation at a particular x value and the relation holds:

$$
\begin{aligned}
\#F(x_0) &= \sum_{i}^{\#F(x_0)}f(x_0)+\sum_{j}^{\#N(x_0)}f(x_0) \\
\#F(x_0) &= \sum_{k}^{\#All(x_0)}f(x_0) \\
\#F(x_0) &= (\#F(x_0)+\#N(x_0))\times f(x_0); \quad f(x_0)\equiv\epsilon(x_0) \\
\frac{\#F(x_0)}{(\#F(x_0)+\#N(x_0))} &= \epsilon(x_0)
\end{aligned}
$$

Standard CDF Efficiencies:

Central Tight:

- Efficiencies and Scale Factor combining all the data (> 700 /pb)
  - **Data Efficiency = 0.799 +- 0.002**
  - **MC Efficiency = 0.814 +- 0.001**
  - **Scale Factor = 0.981 +- 0.003 (stat.) +- 0.004 (syst.)**
- Efficiencies and Scale Factor without Isolation cut combining all the data (> 700 /pb)
  - **Data Efficiency = 0.823 +- 0.002**
  - **MC Efficiency = 0.831 +- 0.001**
  - **Scale Factor = 0.990 +- 0.003(stat) +- 0.003(syst)**

Central Loose:

- Efficiencies and Scale Factor combining all the data (> 700 /pb)
  - **Data Efficiency = 0.923 +- 0.001**
  - **MC Efficiency = 0.926 +- 0.001**
  - **Scale Factor = 0.996 +- 0.002(stat) +- 0.004(syst)**

Forward ($1.2 \leq |\eta| \leq 2.8$):

- Efficiencies and Scale Factor combining all the data (> 700 /pb):
  - **Data Efficiency = 0.837 +- 0.003**
  - **MC Efficiency = 0.897 +- 0.001**
  - **Scale Factor = 0.933 +- 0.005(stat) +- 0.012(syst)**

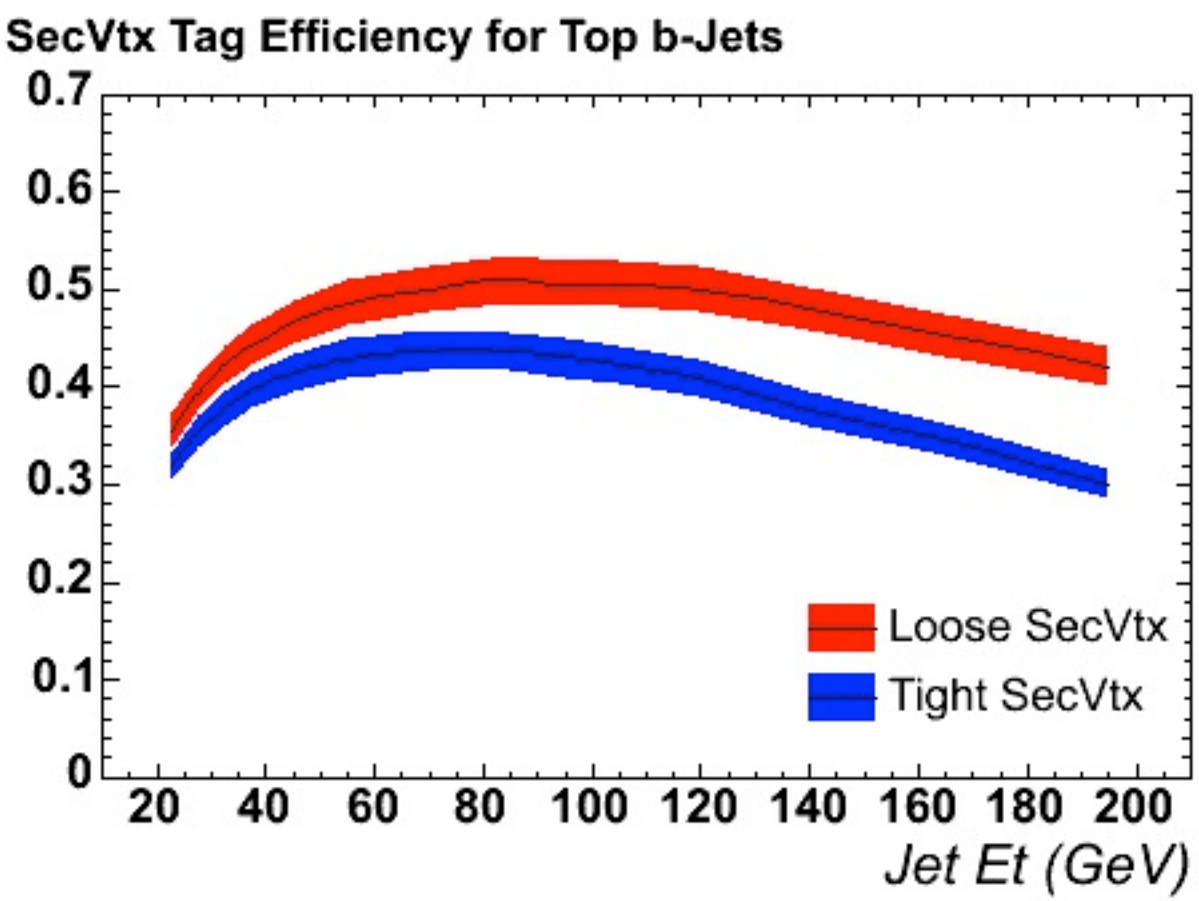
Forward Tight Phoenix:

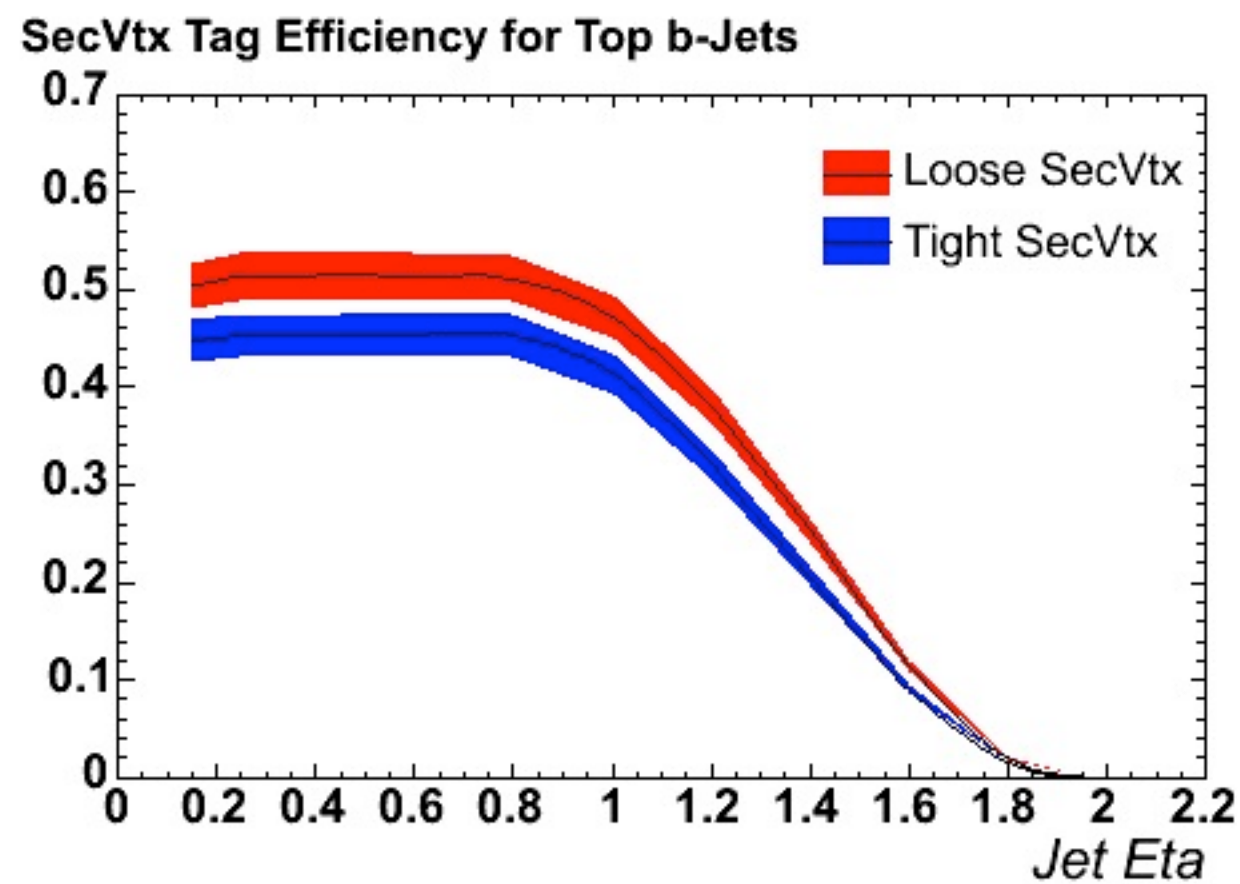
- Efficiencies and Scale Factor combining all the data (> 700 /pb):
  - **Data Efficiency = 0.658 +- 0.004**
  - **MC Efficiency = 0.691 +- 0.001**
  - **Scale Factor = 0.952 +- 0.006(stat) +- 0.012(syst)**

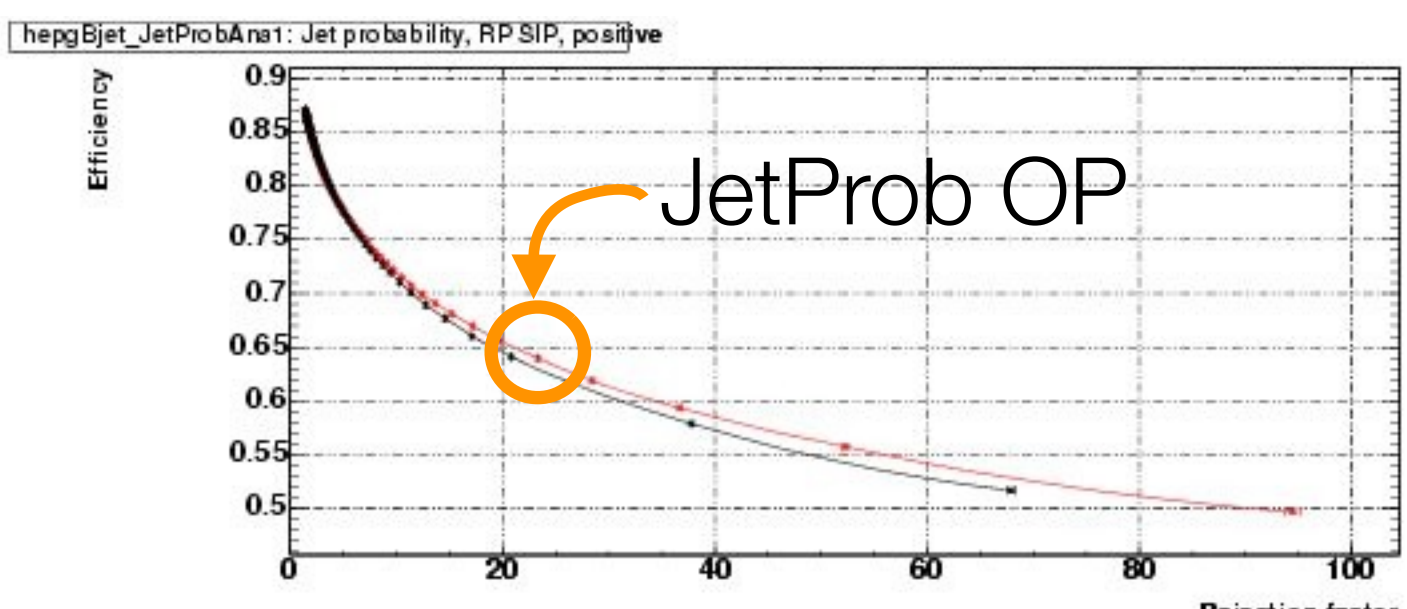
Forward Tight Phoenix $|\eta|<2$:

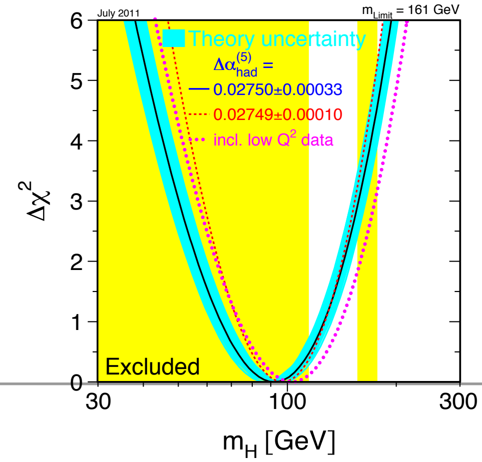
- Efficiencies and Scale Factor combining all the data (> 700 /pb):
  - **Data Efficiency = 0.730 +- 0.004**
  - **MC Efficiency = 0.775 +- 0.001**
  - **Scale Factor = 0.942 +- 0.005(stat) +- 0.012(syst)**

B-Tagging Efficiencies

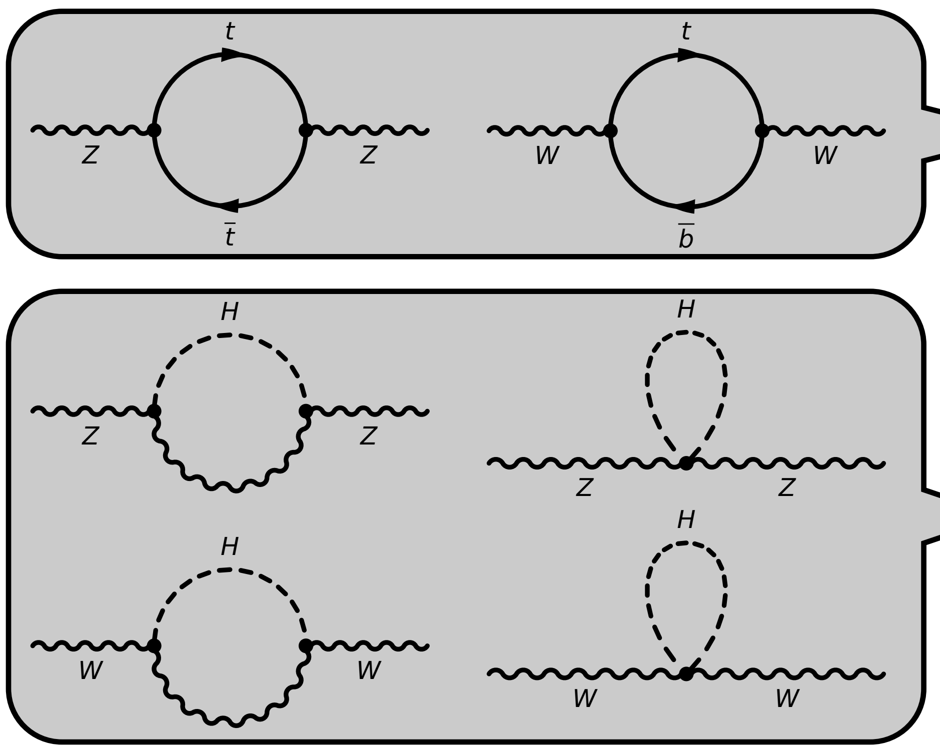






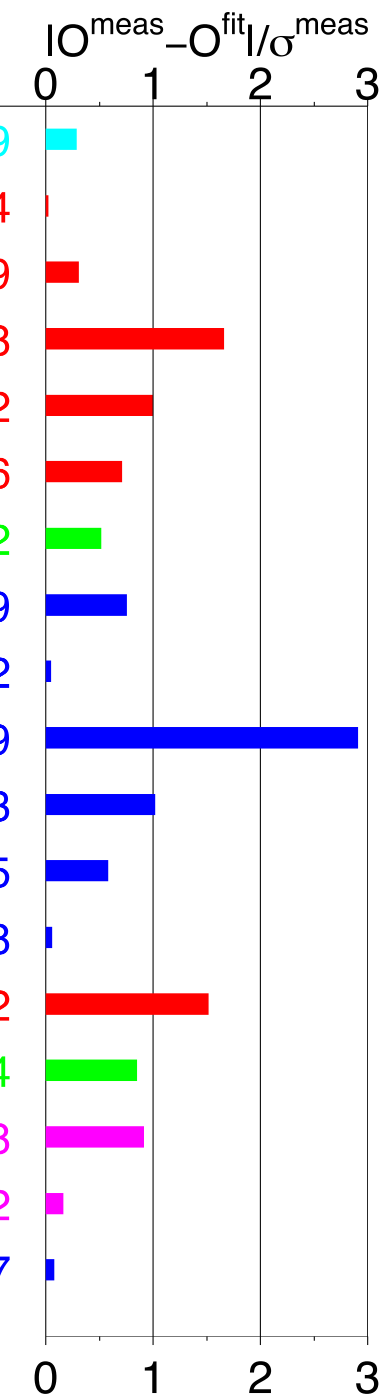
What's Going on Here:  ?

- Precision electroweak measurements predict the Higgs mass by determining radiative corrections which are sensitive to m_H



- **m_t, m_W**, m_Z, Γ_W, **hadronic vacuum polarization** ($\Delta\alpha^{(5)}_{had}$), and Z pole data (asymmetry factors, ratio of widths,...) go into the fit

	Measurement	Fit
$\Delta\alpha^{(5)}_{had}(m_Z)$	0.02750 ± 0.00033	0.02759
m_Z [GeV]	91.1875 ± 0.0021	91.1874
Γ_Z [GeV]	2.4952 ± 0.0023	2.4959
σ^0_{had} [nb]	41.540 ± 0.037	41.478
R_l	20.767 ± 0.025	20.742
$A^{0,l}_{fb}$	0.01714 ± 0.00095	0.01646
$A_l(P_\tau)$	0.1465 ± 0.0032	0.1482
R_b	0.21629 ± 0.00066	0.21579
R_c	0.1721 ± 0.0030	0.1722
$A^{0,b}_{fb}$	0.0992 ± 0.0016	0.1039
$A^{0,c}_{fb}$	0.0707 ± 0.0035	0.0743
A_b	0.923 ± 0.020	0.935
A_c	0.670 ± 0.027	0.668
A_l(SLD)	0.1513 ± 0.0021	0.1482
$\sin^2\theta^{lept}_{eff}(Q_{fb})$	0.2324 ± 0.0012	0.2314
m_W [GeV]	80.399 ± 0.023	80.378
Γ_W [GeV]	2.085 ± 0.042	2.092
m_t [GeV]	173.20 ± 0.90	173.27



July 2011

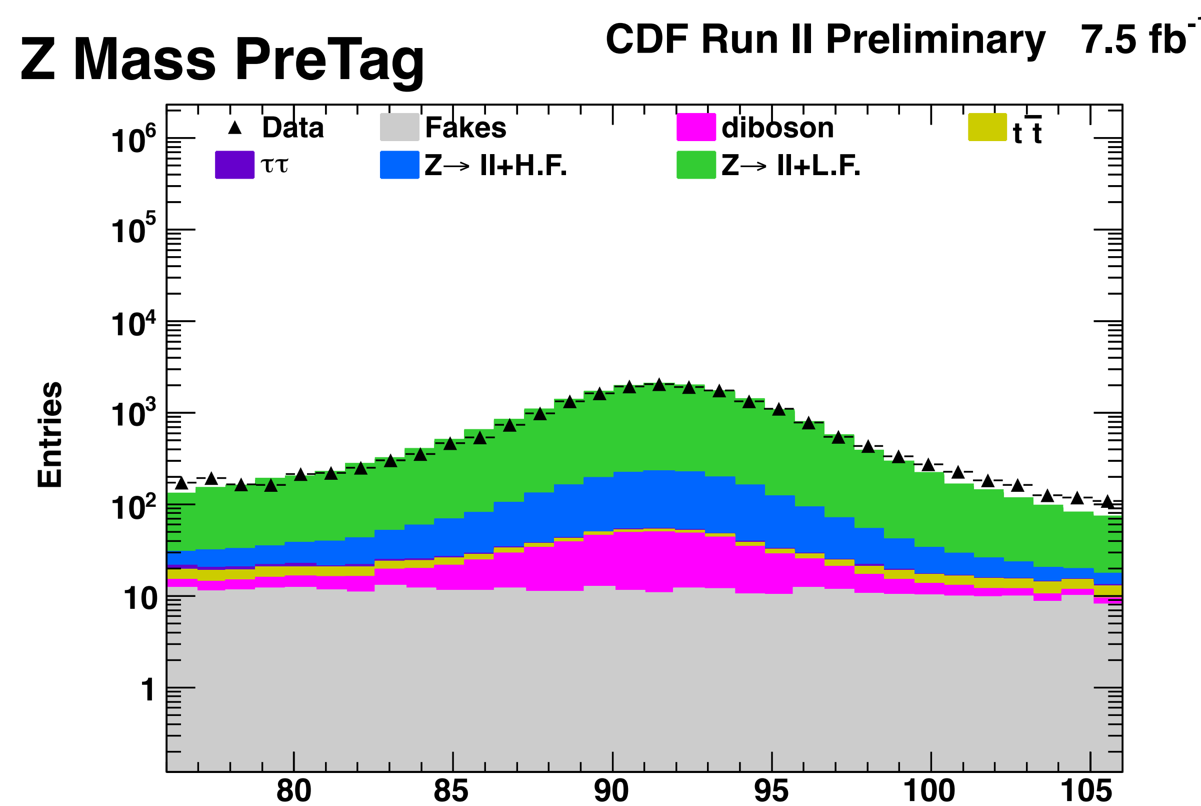
Trigger Requirements

Trigger Name	Level 1	Level 2	Level 3
ELECTRON CENTRAL 18	$E_T \geq 8$ Gev Had/Em < 0.125 Track $P_T \geq 8.34$	cluster $\lvert\eta\rvert < 1.317$ cluster $E_T \geq 18$ GeV cluster Had/Em ≤ 0.125	$E_T \geq 18$ GeV Had/Em ≤ 0.125 central calorimeter Track $P_T \geq 9$ GeV Lshr < 0.4 $\Delta Z < 8$ cm
Z NOTRACK	$E_T \geq 18$ Gev Central Had/Em ≤ 0.125 Plug Had/Em ≤ 0.0625 two objects	cluster $\lvert\eta\rvert < 3.6$ cluster $E_T \geq 16$ Gev cluster Had/Em ≤ 0.125 two clusters	two objects $E_T \geq 18$ GeV
Z NOTRACK MASS	$E_T \geq 18$ Gev Central Had/Em ≤ 0.125 Plug Had/Em ≤ 0.0625 two objects	$E_{T1} \geq 16$ GeV $E_{T2} \geq 8$ GeV Had/Em ≤ 0.125 Mass$(e_1, e_2) \geq 40$ GeV/c^2	$E_{T1} \geq 18$ GeV $E_{T2} \geq 9$ GeV Had/Em ≤ 0.125

Table 4.1: Many of the requirements for the three electron triggers to pass each trigger level. An event passing level 3 is saved to mass storage and considered in this analysis. The "no track" label in a trigger name does not require a trackless object, but rather only takes into account calorimeter quantities in the trigger decision.

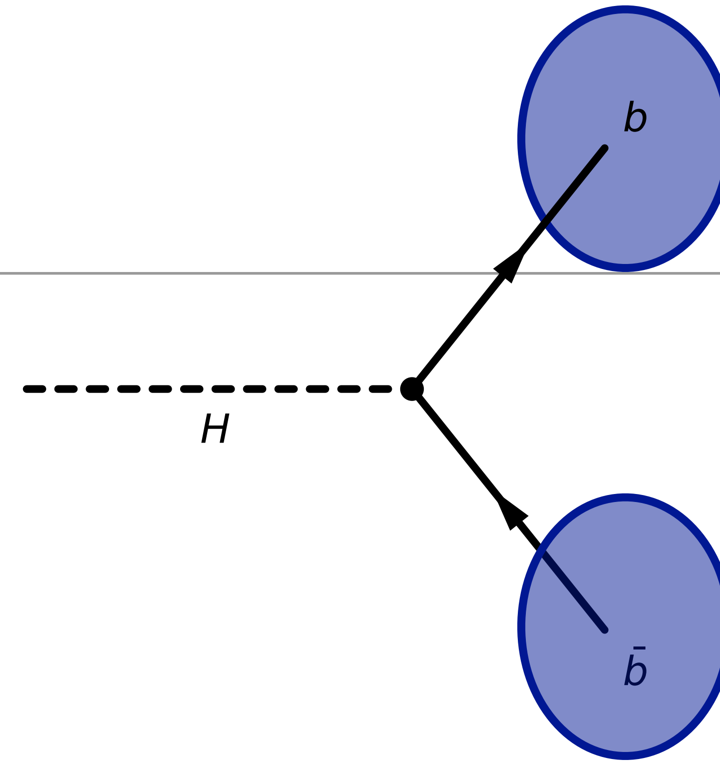
Modeling Events Due to Misidentified Electrons

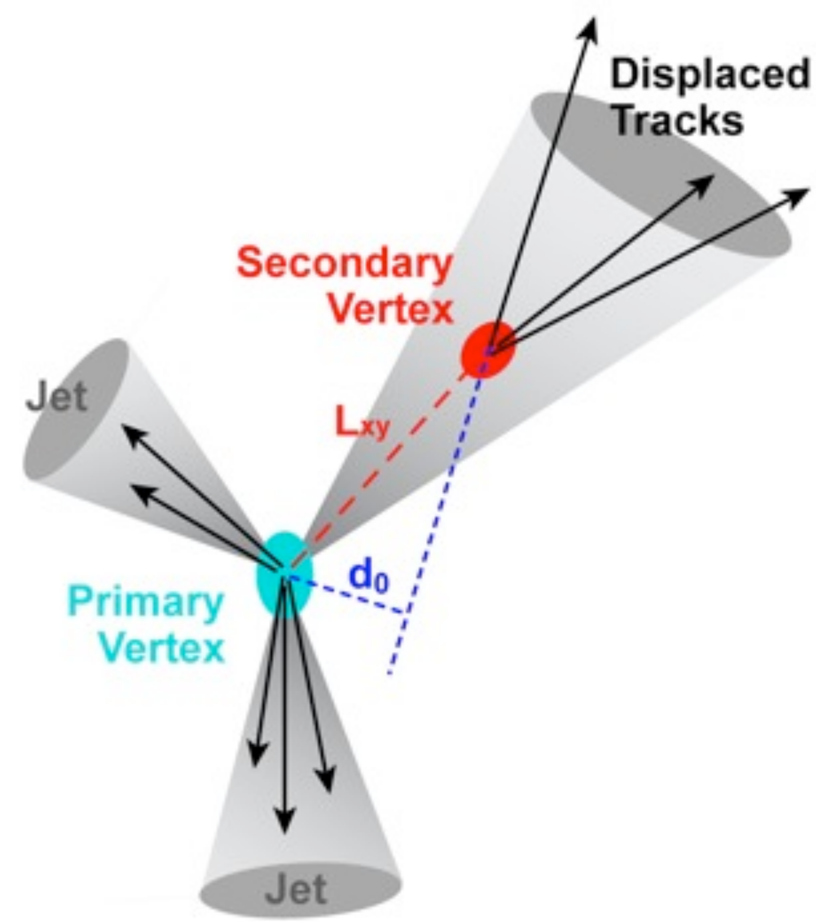
- All electron plus jet pairs are considered as events with a weight equal to the fake rate of the jet
  - This should already have "double fake" events where the electron is really a fake
  - The neural network selection reduces the fake rate (8% to 1.6% of events at pretag)



Jet Selection

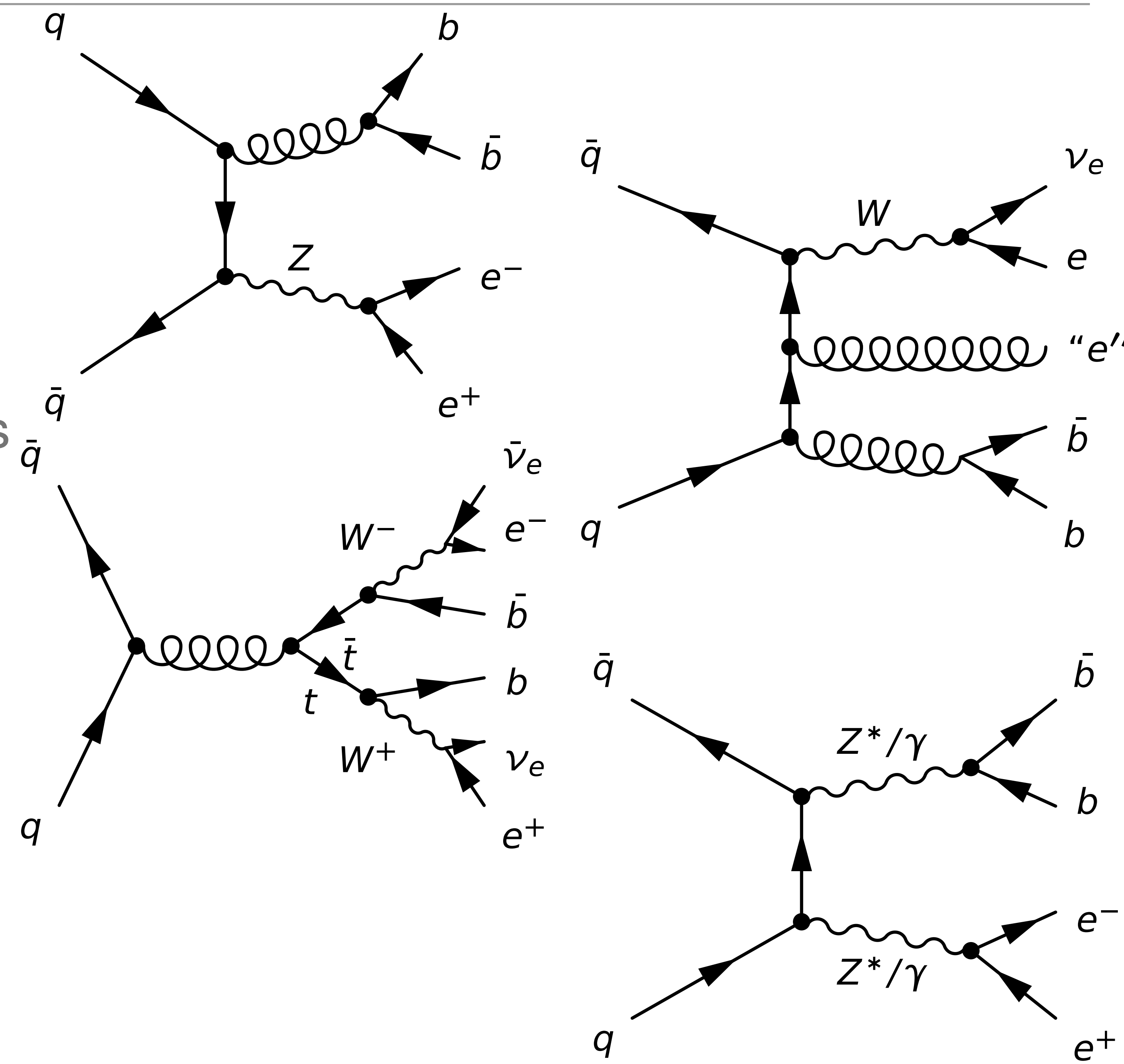
- Require **two jets** for H to bb
- $|\eta_{det}|<2$ and $E_T(jet_1,jet_2)>25$, 15 GeV
  - **Pretag**: this is the high-statistics (25 x events) model validation region
  - ***b* tag**: *b* quarks live long enough to hadronize producing a displaced vertex -- finding this is *b tagging*
- Apply *b* tagging to the pretag sample
  - **3 final analysis channels**:
    - Double tight tagged
    - Double loose tagged
    - Single tight tagged





Main Backgrounds

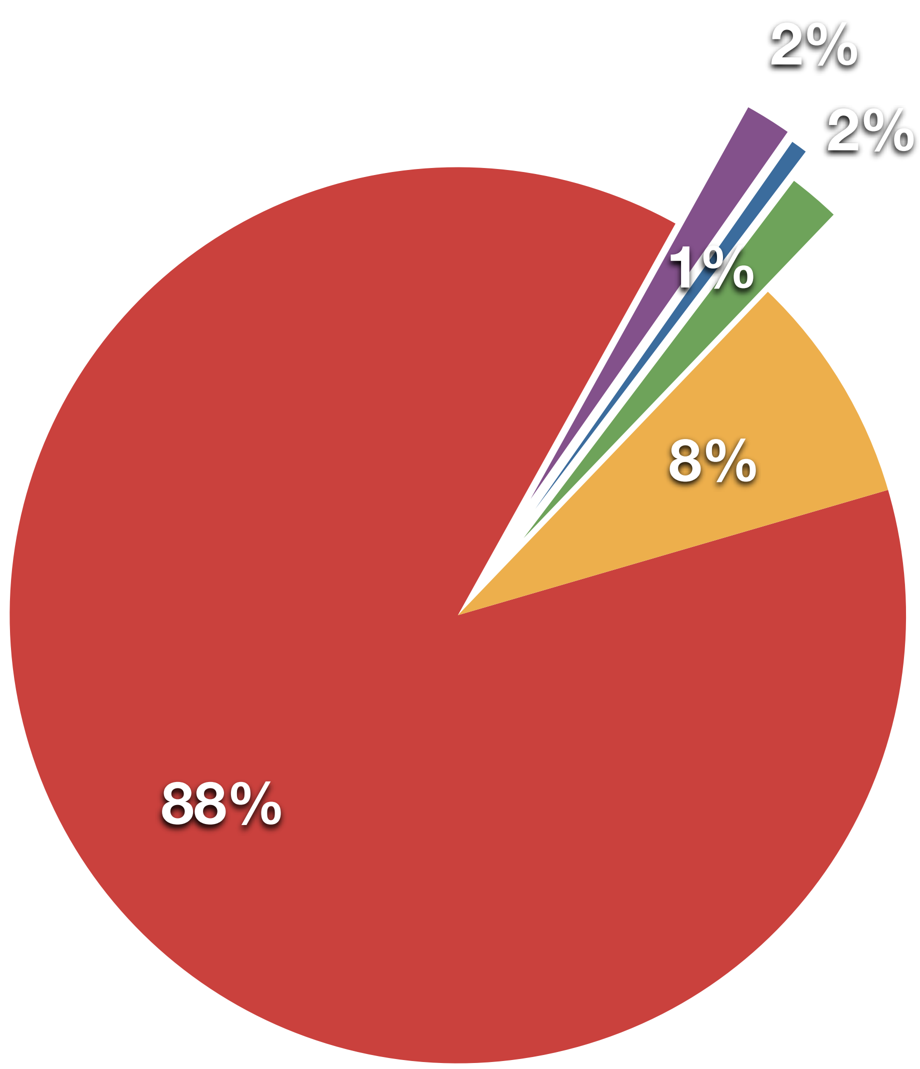
- Processes that mimic the 2 electron + 2 jet signature
  - Z + 2 jet
  - Misidentified objects (electrons = fakes, b jets = mistags)
  - ttbar
  - diboson (ZZ, WZ, some WW + jets)



Main Backgrounds

- Pretag is dominated by light flavor (lf) jets

  - ttbar
  - Diboson
  - Z+hf jets
  - Z+lf jets
  - Fakes



Main Backgrounds

- Pretag is dominated by light flavor (lf) jets
    - ttbar
    - Diboson
    - Z+hf jets
    - Z+lf jets
    - Fakes

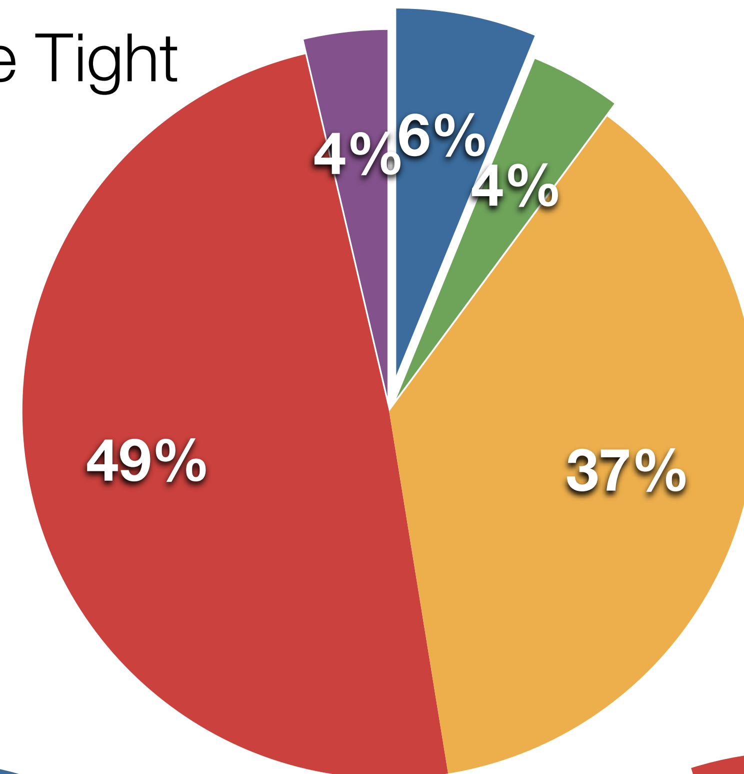
Main Backgrounds

- Pretag is dominated by light flavor (lf) jets

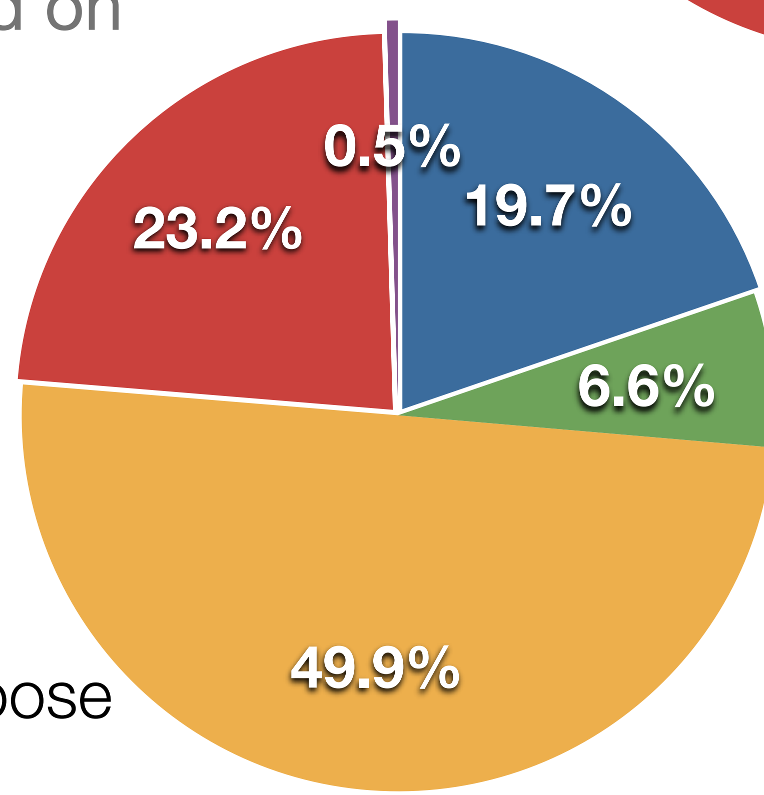
  - ttbar
  - Diboson
  - Z+hf jets
  - Z+lf jets
  - Fakes

- Final analysis channels have varying backgrounds based on *b*-tag combination

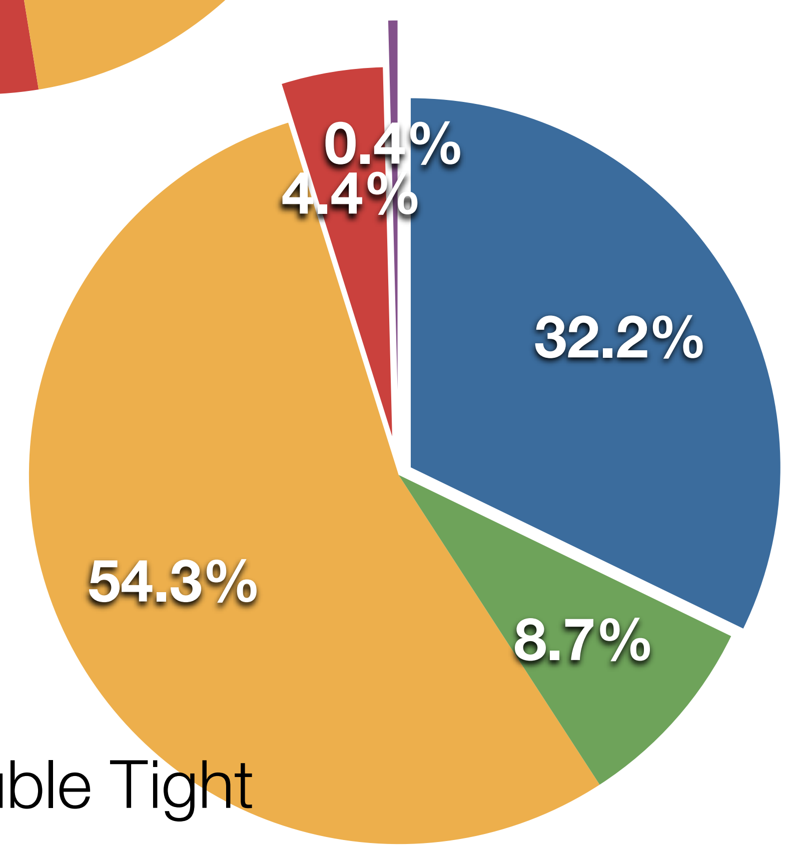
Single Tight



Double Loose



Double Tight



Model

- To test the hypotheses, we of course need a model
- Monte Carlo (MC) and data-driven methods are used
  - Data-driven methods better describe mistakes

- Misidentified electrons (fakes)
- Misidentified *b* jets (mistags)

Process	Generator	σ
Z+l.f.	ALPGEN+PYTHIA	4.66 fb to 2111 pb
$Z+c\bar{c}$	ALPGEN+PYTHIA	148.4 to 1512 fb
$Z+b\bar{b}$	ALPGEN+PYTHIA	53.9 to 715.4 fb
WW	PYTHIA	11.34 pb
WZ	PYTHIA	3.47 pb
ZZ	PYTHIA	3.62 pb
$t\bar{t}$	PYTHIA	7.04 pb

M_H (GeV/c^2)	σ(fb)	$BR(H \rightarrow b\bar{b})$
100	169.8	0.8033
105	145.9	0.7857
110	125.7	0.7590
115	103.9	0.7195
120	90.2	0.6649
125	78.5	0.5948
130	68.5	0.5118
135	60.0	0.4215
140	52.7	0.3304
145	46.3	0.2445
150	40.8	0.1671

Model Validation: Acceptance Tables

High-statistics model-validation region:

PreTag Event Yields
$ZH \to e^+e^-b\bar{b}$ Analysis
CDF Run II Preliminary (7.5 fb^{-1})

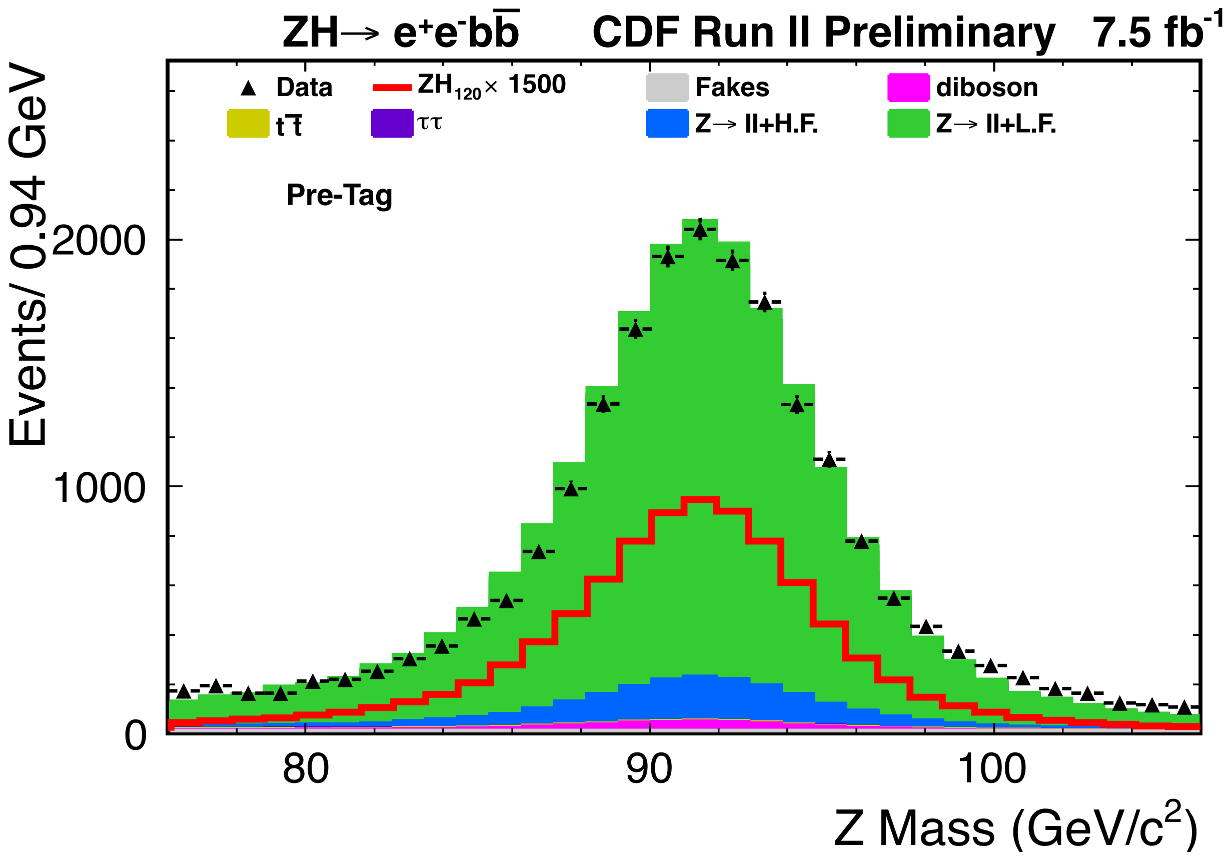
Data	21122
$t\bar{t}$	126 ± 17
Diboson	397 ± 34
$Z/\gamma^* \to ee$ + h.f.	1786 ± 561
$Z/\gamma^* \to ee$ + l.f.	18783 ± 4229
Fakes	354 ± 177
Model	21446 ± 4300

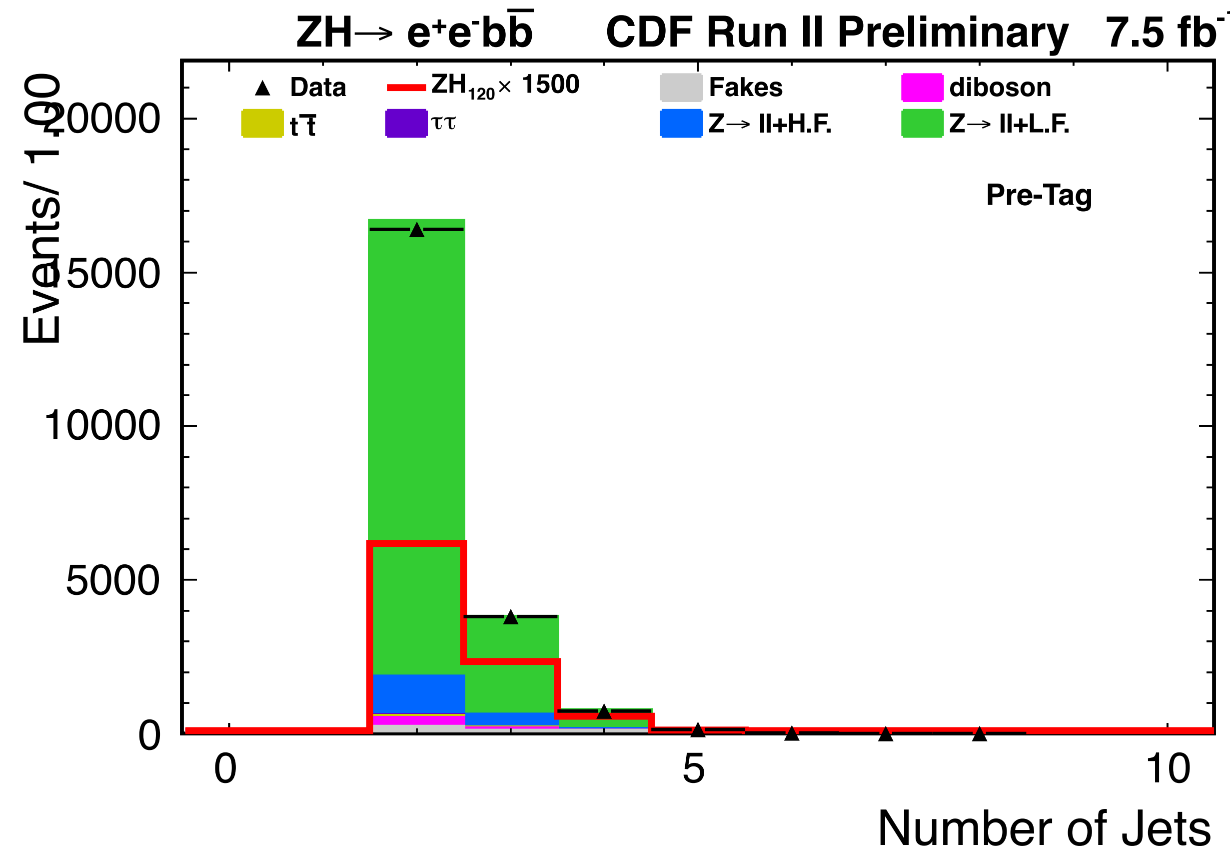
Final Analysis Channels:

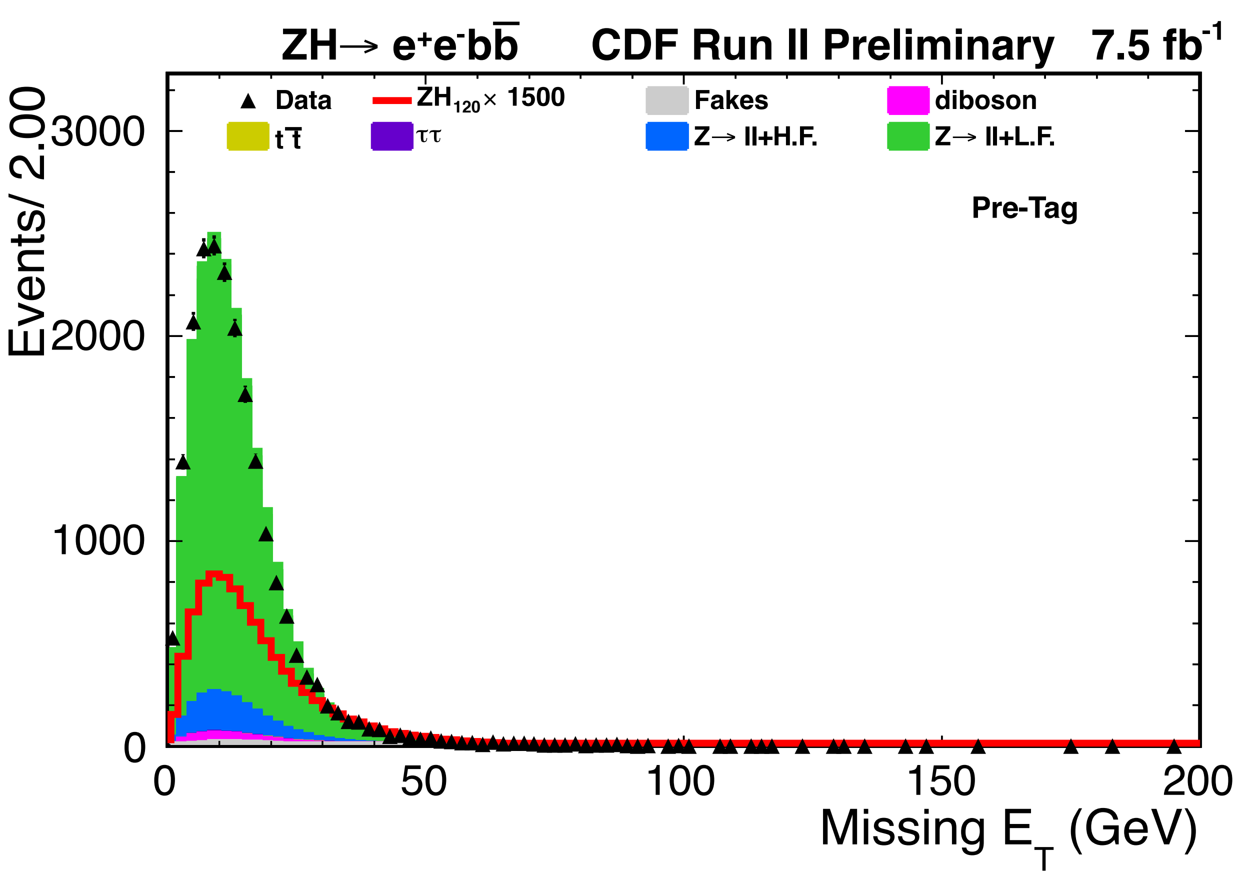
Tag Level Event Yields
$ZH \to e^+e^-b\bar{b}$ Analysis CDF Run II Preliminary (7.5 fb^{-1})

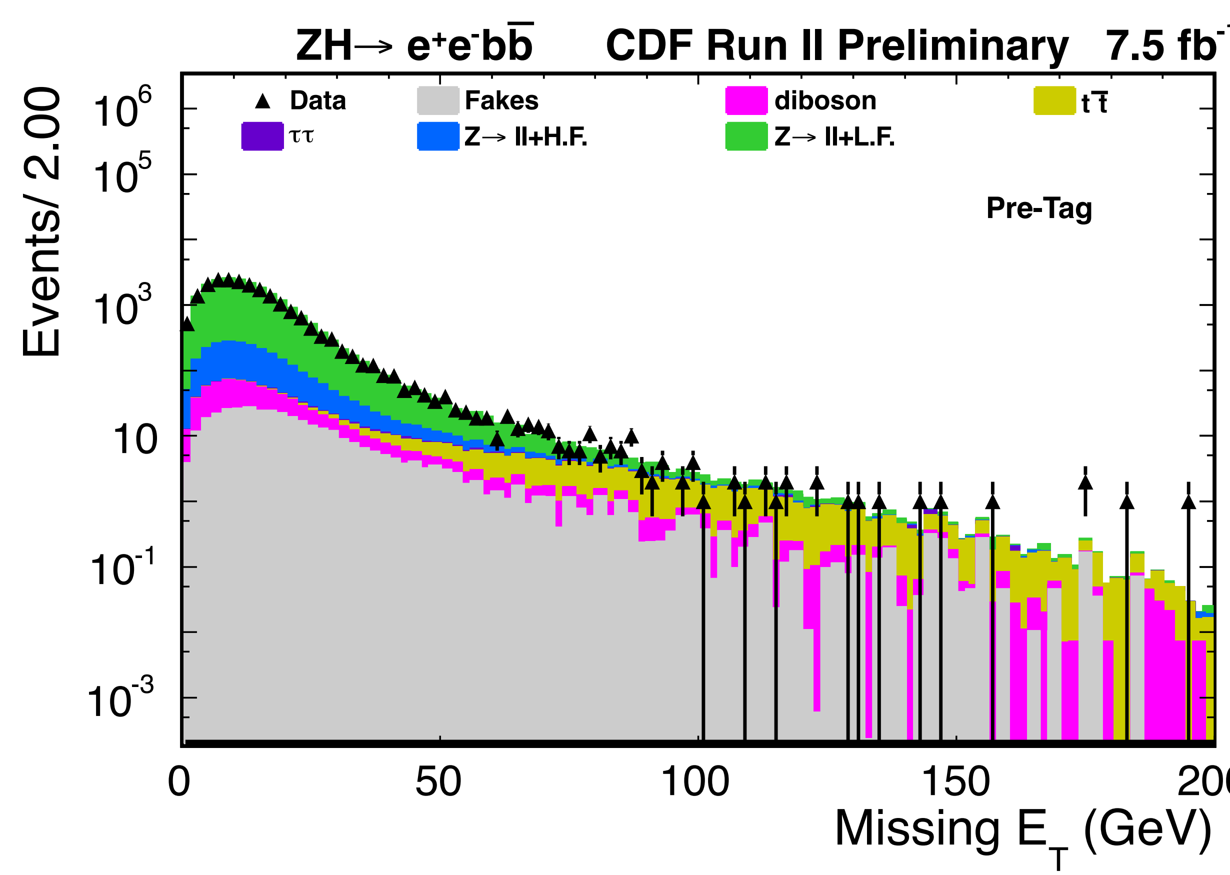
	Single Tight Tag	Loose Double Tag	Double Tight Tag
Data	693	87	51
ZH_{120}	2.0 ± 0.2	0.8 ± 0.1	0.9 ± 0.1
$t\bar{t}$	42 ± 6	17 ± 2	16 ± 3
Diboson	27 ± 3	5.7 ± 0.7	4.3 ± 0.6
$Z/\gamma^* \to ee$ + h.f.	254 ± 81	43 ± 14	27 ± 10
Mistags	333 ± 47	20 ± 5	2.2 ± 0.6
Fakes	25 ± 12	0.4 ± 0.2	0.2 ± 0.1
Model	681 ± 120	86 ± 20	50 ± 13

Model Validation: Plots (Pretag)







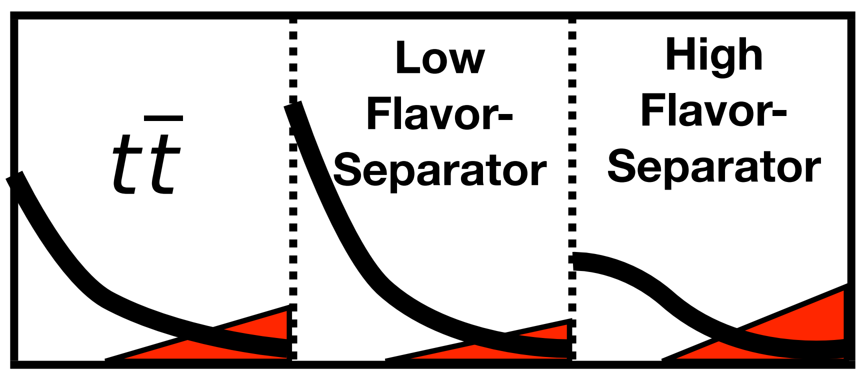


Final Discriminant

- The final discriminant is a neural-network output

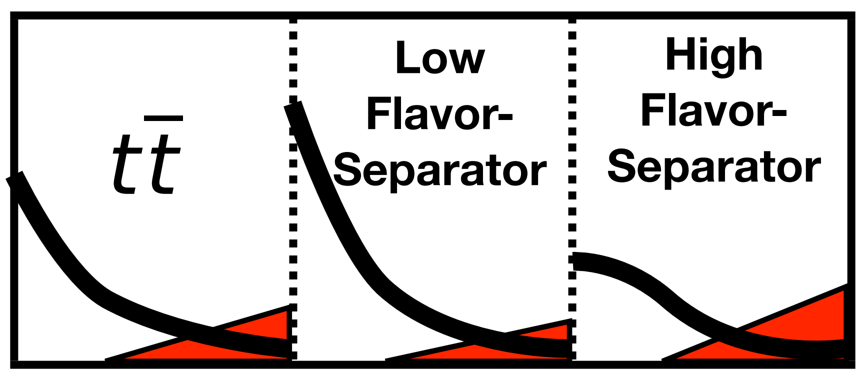
Final Discriminant

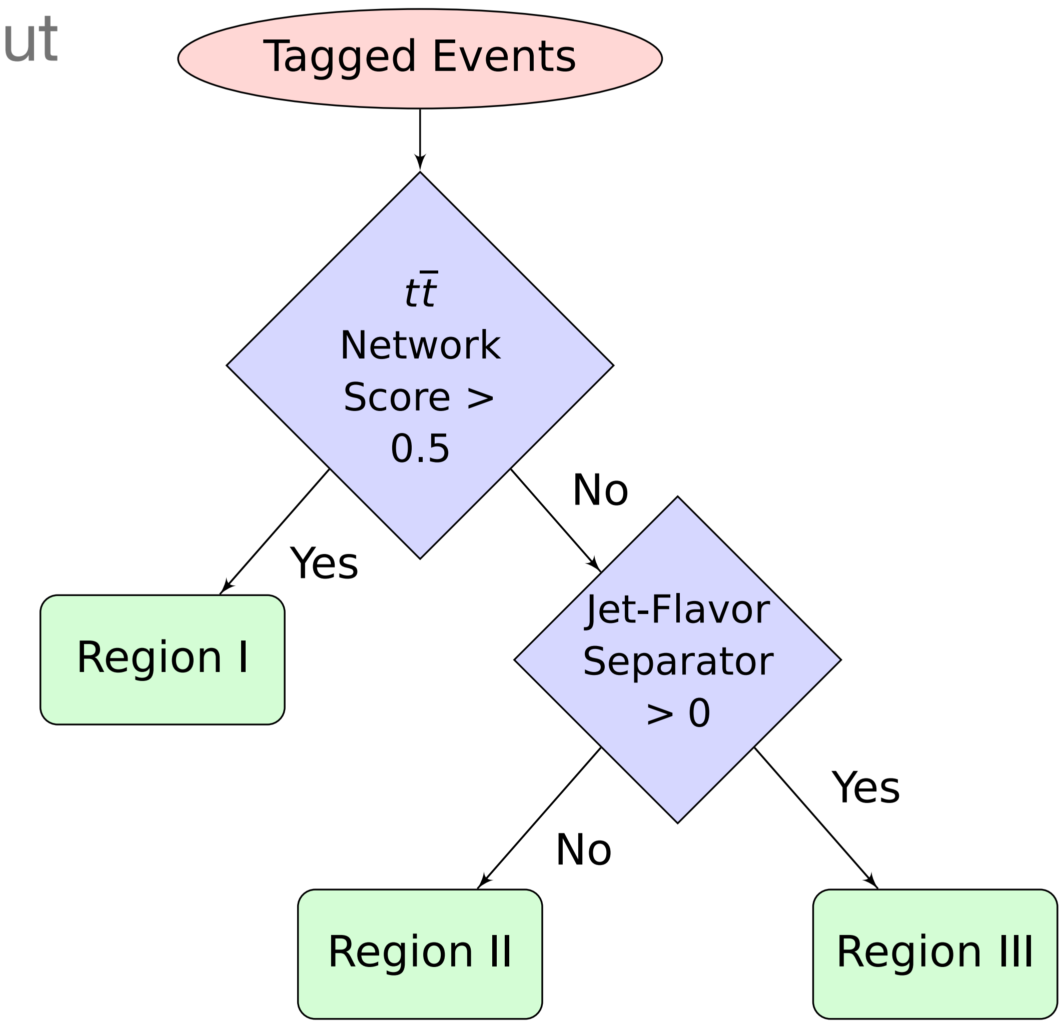
- The final discriminant is a neural-network output
- To improve discrimination, the output is separated into three regions:



Final Discriminant

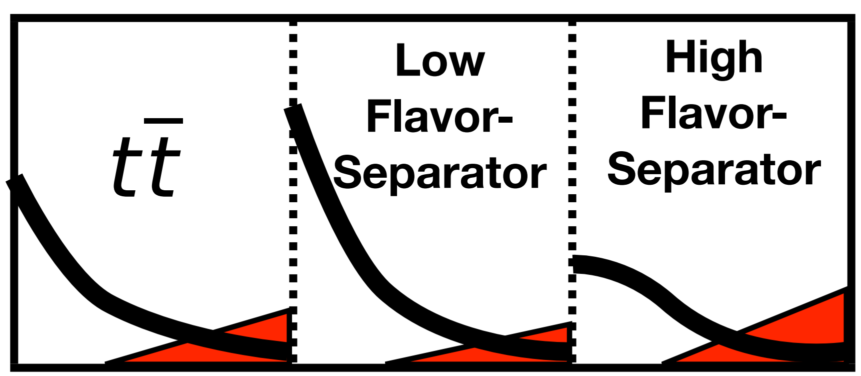
- The final discriminant is a neural-network output
- To improve discrimination, the output is separated into three regions:

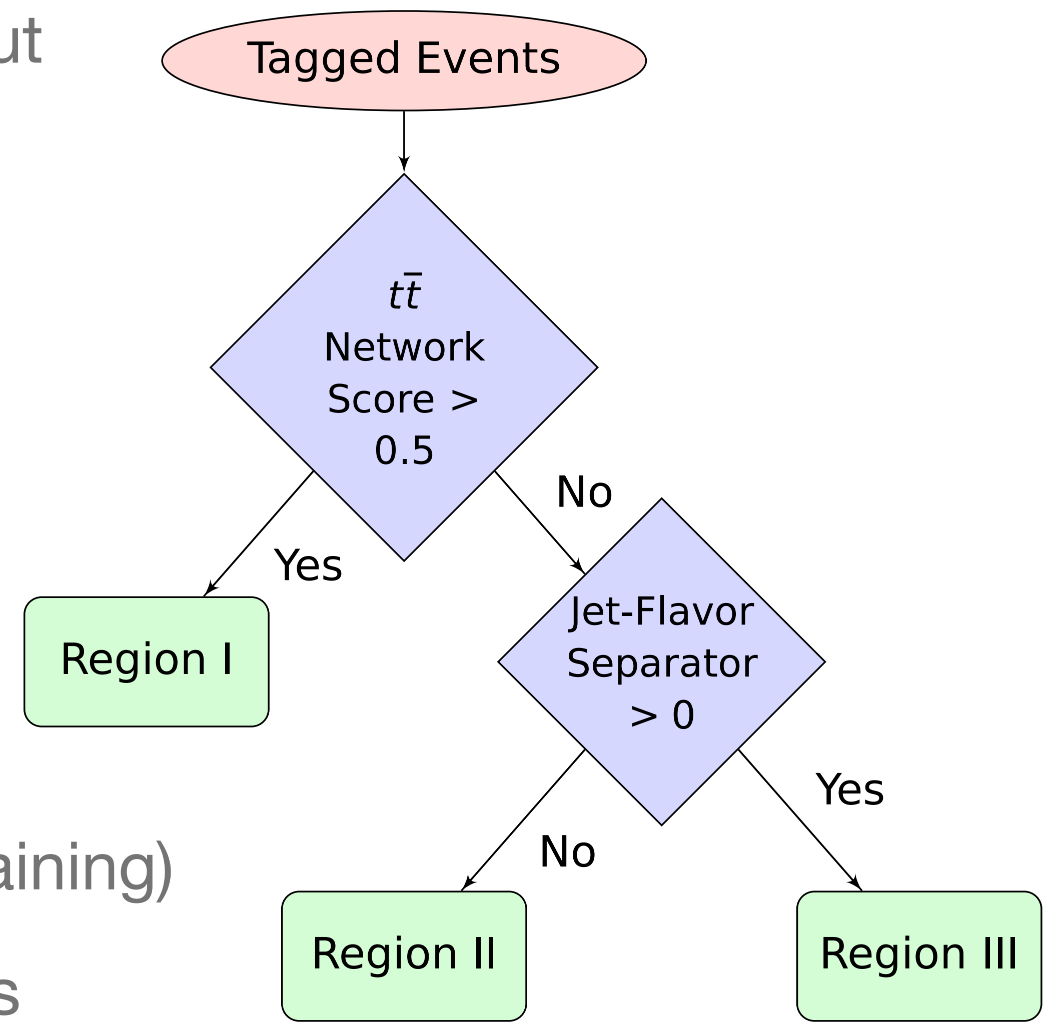




Final Discriminant

- The final discriminant is a neural-network output
- To improve discrimination, the output is separated into three regions:





- Training used tag-level MC (no signs of over-training)
- Variables used were selected in earlier analyses (iterative approach) and BDT outputs were added
- Network applied is the same for the three regions and for each tag category, BUT *a different network is trained for each mass hypothesis*

Final Discriminant: Input Variables

- Network variables taken from those selected by previous analyses.

•Energy BDT	•$\Delta R(j_2,Z)$
•Shape BDT	•M_{jj}
•$\Delta R(e_1,e_2)$	•MET
•Twist e_1e_2	•Z.Et() + jj.Et()
•Sphericity	•jj.Pt()
•$\Delta\phi(bb)$	•Z P_T
•$\cos(\theta^*)$	•MET proj. All Jets

Final Discriminant: Input Variables

- Network variables taken from those selected by previous analyses.
- We had a large number of well-modeled distributions to distinguish S & B

Shape BDT	Energy BDT
$\Delta R(e_1, e_2)$	Dijet Mass
$\not{E}_T$ proj. onto vector $\Sigma(jets)$	$\not{E}_T$
$\Delta R(j1, j2)$	$\not{E}_T/\sqrt{(}j_1E_T + j_2E_T)$
$\Delta R(Z, DijetObject)$	$\not{E}_T/\sqrt{(}\Sigma$ jet $E_T)$
Aplanarity	sigExtraEt=ZE_T+Dijet E_T
Sphericity	Dijet P_T
$\Delta\eta(j_1, j_2)$	Mass(e_1, j_1)
Twist(e_1, e_2)	Mass(e_2, j_2)
Twist(j_1, j_2)	Z P_T
$\Delta\phi(j1, j2)$	Mass(Z,jj)
$\Delta\theta(\not{E}_T$,$j_1)$ in Z rest frame	Number of jets
$\Delta\theta(\not{E}_T$,$j_2)$ in Z rest frame	J_1E_T
$\Delta\theta(\not{E}_T$,$e_1)$ in H rest frame	J_2E_T
$\Delta\theta(\not{E}_T$,$e_2)$ in H rest frame	$\not{E}_T$ + el. E_T's + jet E_T's
$\not{E}_T$ projection onto jet 1	$\not{E}_T$ + lepton E_T's
$\not{E}_T$ projection onto jet 2	$\Delta E_T(j_1, j_2)$
$Z\eta$	e_1E_T
$j_1\eta$	e_2E_T
$j_2\eta$	
$\Delta R(j_1, Z)$	
$\Delta R(j_2, Z)$	
$\cos(\theta*)$	
$\cos(\chi\vert\xi = \pi/2)$	
$\cos(\theta jet_1)$ in Z rest Frame	
$\cos(\theta jet_2)$ in Z rest Frame	
$\cos(\theta e_1)$ in H rest Frame	
$\cos(\theta e_2)$ in H rest Frame	

Table 1: Distributions input to the BDT's. Twist(x_1, x_2) = $\tan^{-1}(\Delta\phi(x_1, x_2)/\Delta\eta(x_1, x_2))$ [**?**]. θ is the angle between an object and the proton beam direction. $\theta*$ is the angle between the Z boson candidate and the proton beam direction in the zero momentum frame. The sum of the angles χ and ξ is equal to the angle between the Higgs candidate and the lead P_T lepton in the Z boson rest frame.

- Energy BDT
- Shape BDT
- $\Delta R(e_1,e_2)$
- Twist e_1e_2
- Sphericity
- $\Delta\phi$(bb)
- $\cos(\theta^*)$
- $\Delta R(j_2,Z)$
- M_{jj}
- MET
- Z.Et() + jj.Et()
- jj.Pt()
- Z P_T
- MET proj. All Jets

Final Discriminant: Input Variables

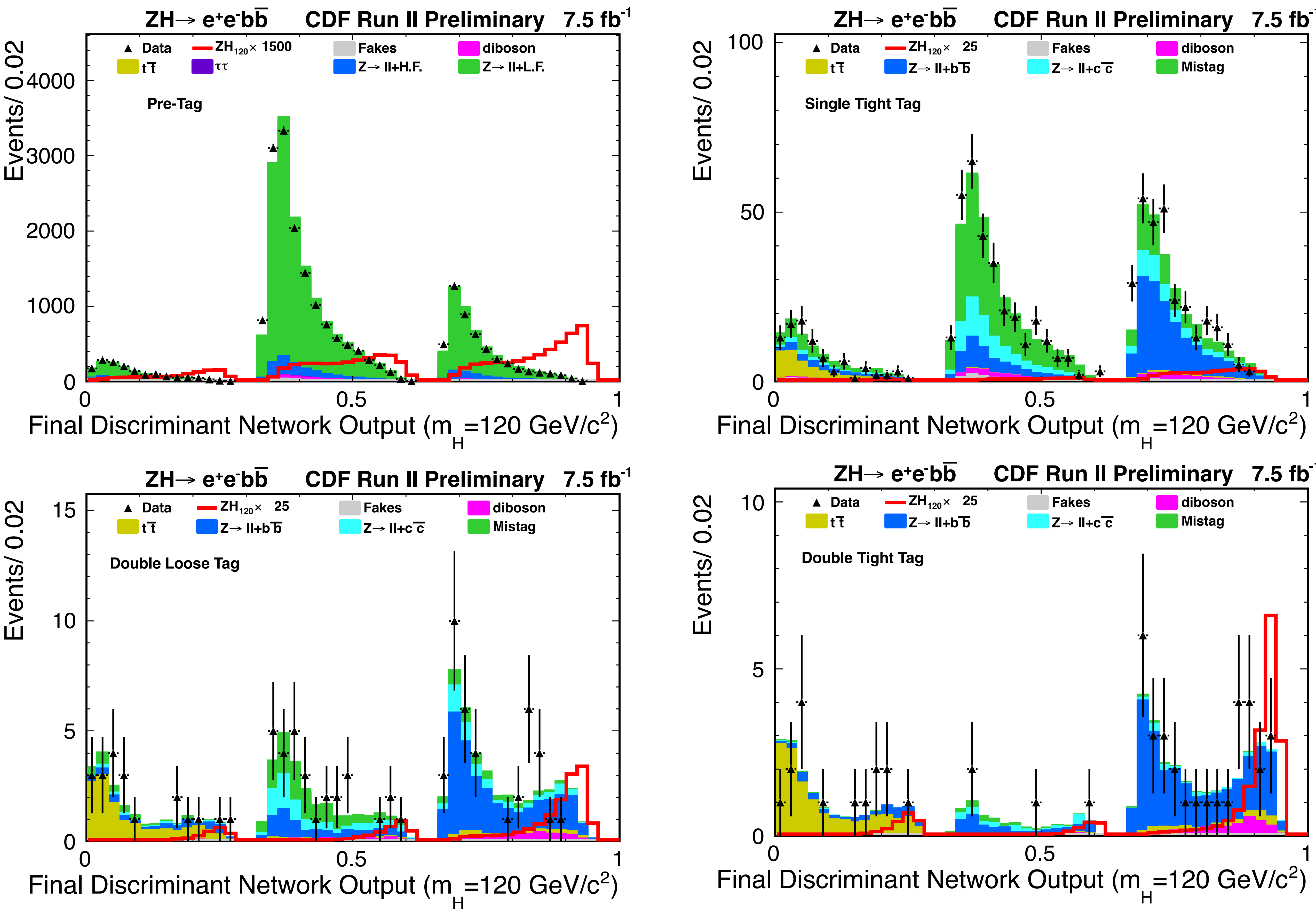
- Network variables taken from those selected by previous analyses.
- We had a large number of well-modeled distributions to distinguish S & B
  - Network performance drops after a few variables are added
  - Instead, developed BDTs (bagged)

Shape BDT	Energy BDT
$\Delta R(e_1, e_2)$	Dijet Mass
$\not{E}_T$ proj. onto vector $\Sigma(jets)$	$\not{E}_T$
$\Delta R(j1, j2)$	$\not{E}_T/\sqrt{(j_1 E_T + j_2 E_T)}$
$\Delta R(Z, DijetObject)$	$\not{E}_T/\sqrt{(\Sigma \text{ jet } E_T)}$
Aplanarity	sigExtraEt=ZE_T+Dijet E_T
Sphericity	Dijet P_T
$\Delta\eta(j_1, j_2)$	Mass(e_1, j_1)
Twist(e_1, e_2)	Mass(e_2, j_2)
Twist(j_1, j_2)	Z P_T
$\Delta\phi(j1, j2)$	Mass(Z,jj)
$\Delta\theta(\not{E}_T, j_1)$ in Z rest frame	Number of jets
$\Delta\theta(\not{E}_T, j_2)$ in Z rest frame	$J_1 E_T$
$\Delta\theta(\not{E}_T, e_1)$ in H rest frame	$J_2 E_T$
$\Delta\theta(\not{E}_T, e_2)$ in H rest frame	$\not{E}_T$ + el. E_T's + jet E_T's
$\not{E}_T$ projection onto jet 1	$\not{E}_T$ + lepton E_T's
$\not{E}_T$ projection onto jet 2	$\Delta E_T(j_1, j_2)$
$Z\eta$	$e_1 E_T$
$j_1\eta$	$e_2 E_T$
$j_2\eta$	
$\Delta R(j_1, Z)$	
$\Delta R(j_2, Z)$	
$\cos(\theta^*)$	
$\cos(\chi \vert \xi = \pi/2)$	
$\cos(\theta jet_1)$ in Z rest Frame	
$\cos(\theta jet_2)$ in Z rest Frame	
$\cos(\theta e_1)$ in H rest Frame	
$\cos(\theta e_2)$ in H rest Frame	

Table 1: Distributions input to the BDT's. Twist(x_1, x_2) = $\tan^{-1}(\Delta\phi(x_1, x_2)/\Delta\eta(x_1, x_2))$ [**?**]. θ is the angle between an object and the proton beam direction. θ^* is the angle between the Z boson candidate and the proton beam direction in the zero momentum frame. The sum of the angles χ and ξ is equal to the angle between the Higgs candidate and the lead P_T lepton in the Z boson rest frame.

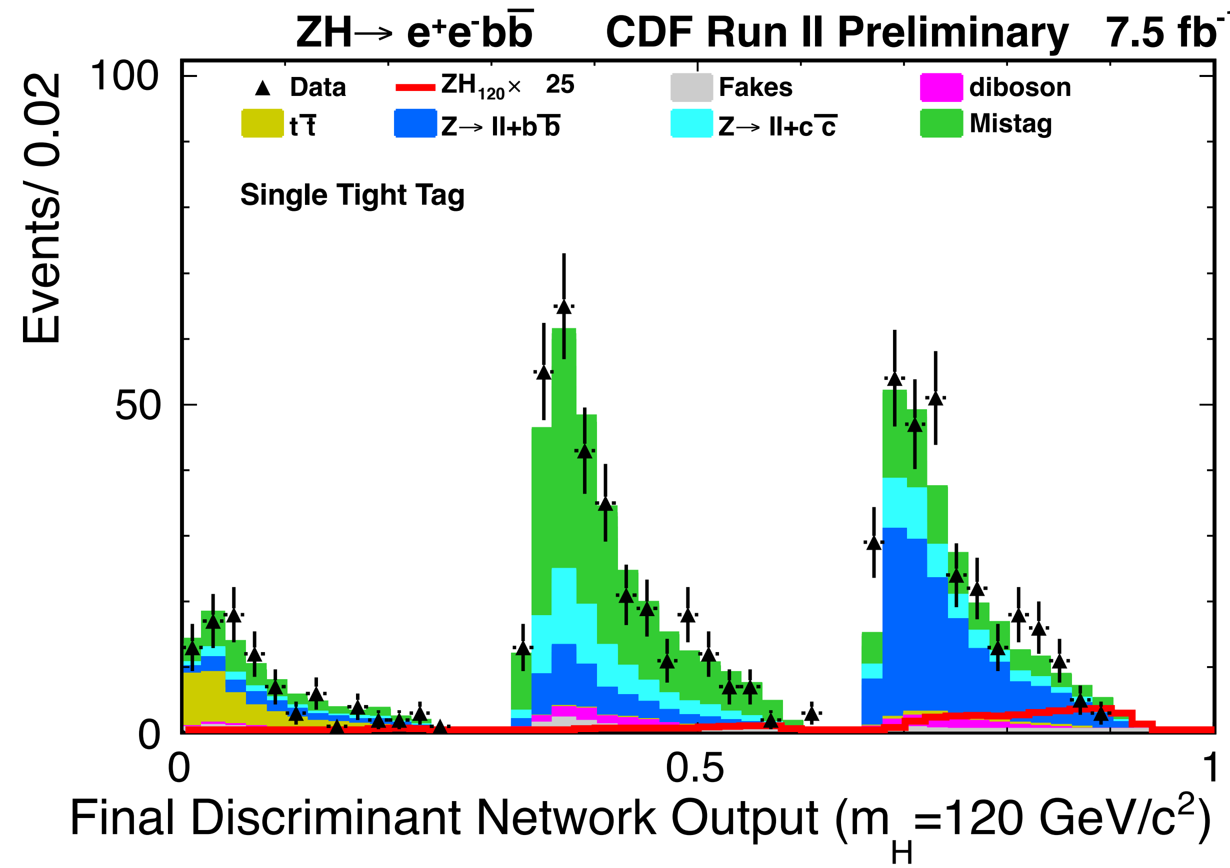
•Energy BDT	•$\Delta R(j_2, Z)$
•Shape BDT	•M_{jj}
•$\Delta R(e_1, e_2)$	•MET
•Twist $e_1 e_2$	•Z.Et() + jj.Et()
•Sphericity	•jj.Pt()
•$\Delta\phi$(bb)	•Z P_T
•$\cos(\theta^*)$	•MET proj. All Jets

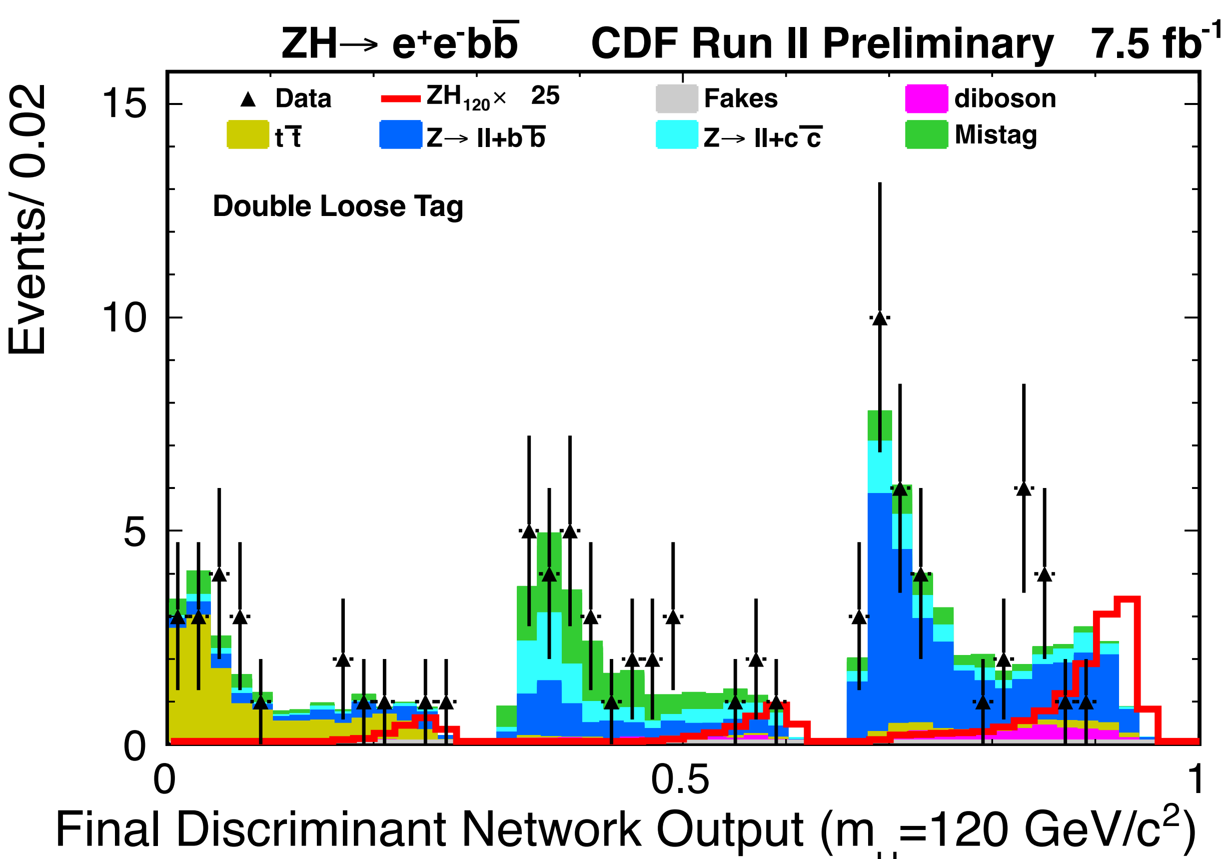
Final Discriminant Outputs (m_H=120 GeV/c^2)

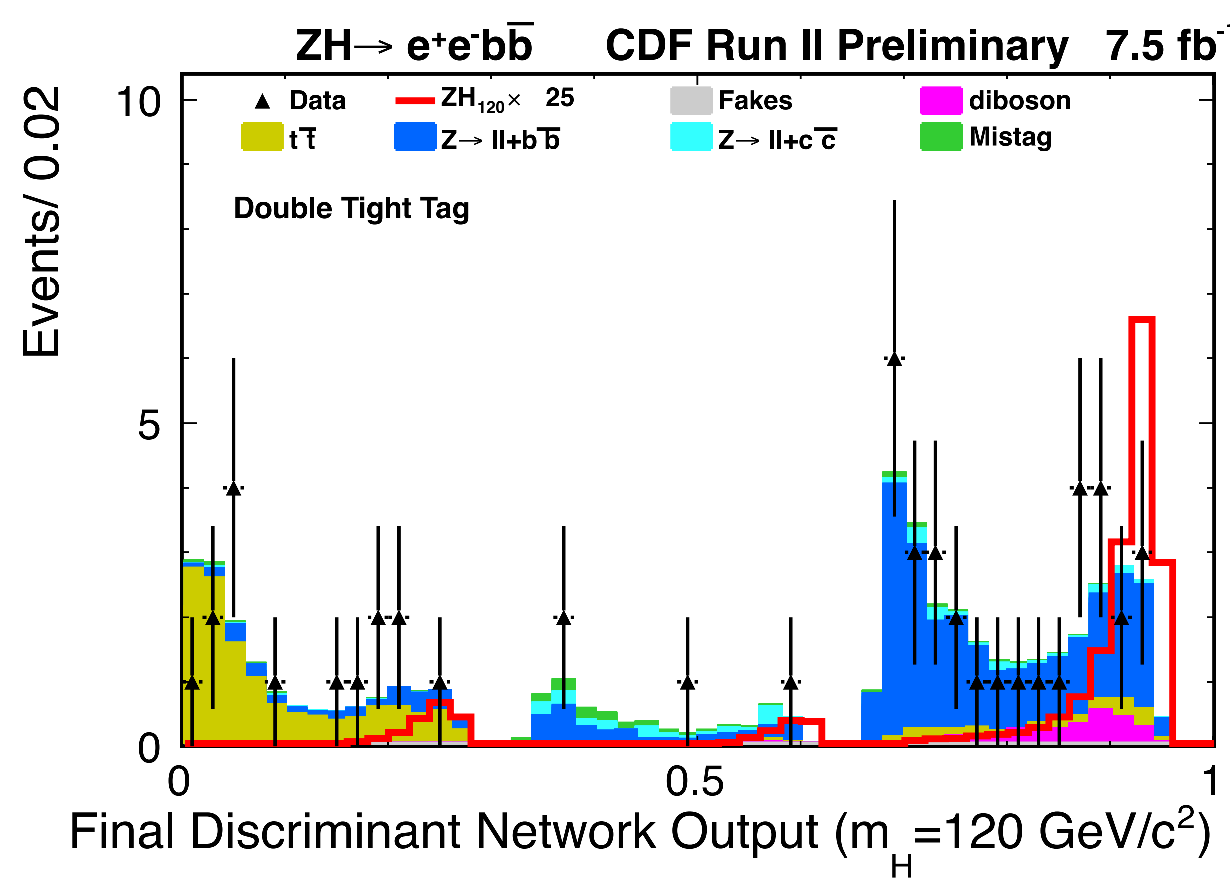


Final Discriminant Outputs (m_H=120 GeV/c^2)

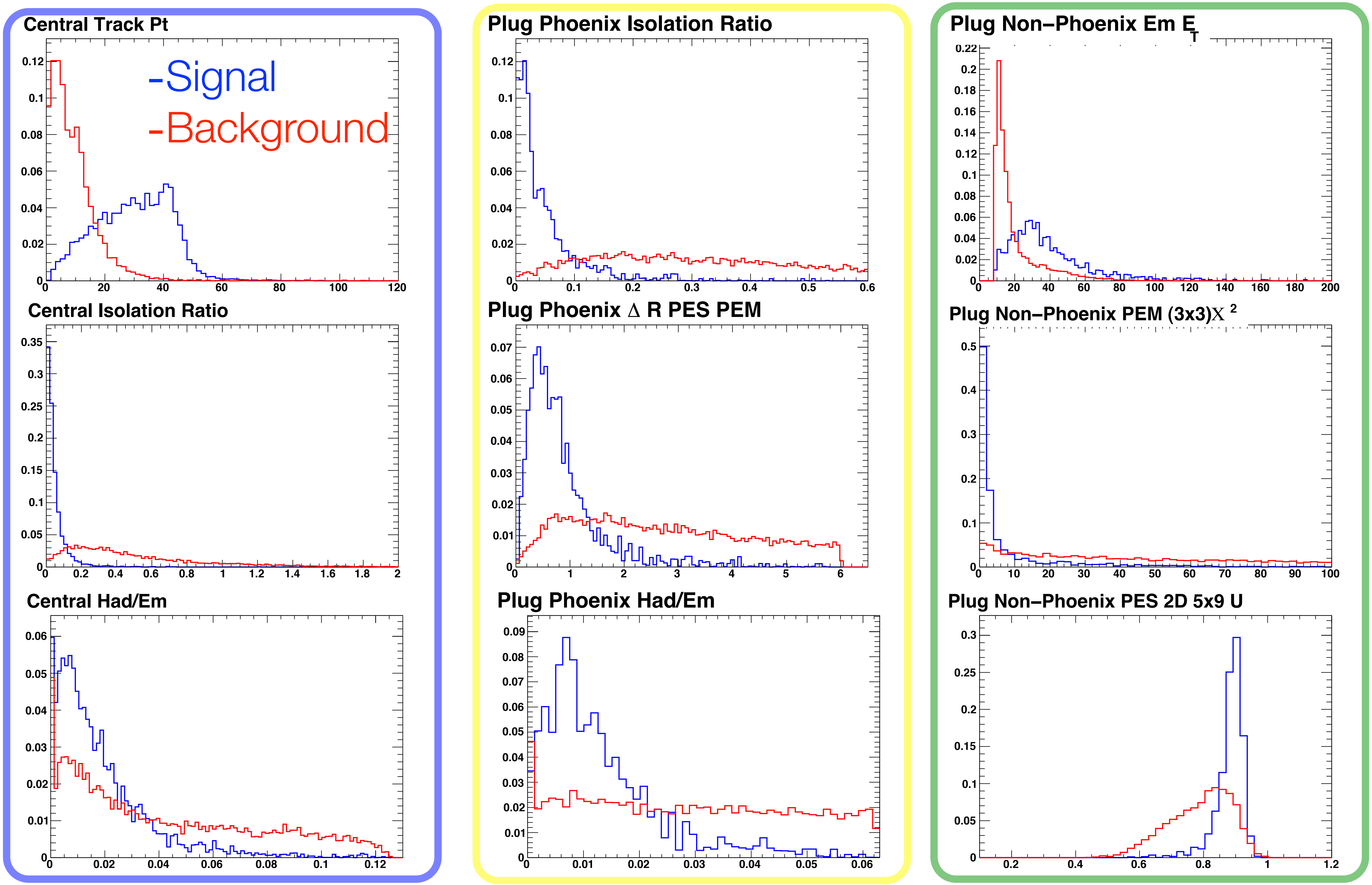
No Higgs excess -- so we proceed to set upper production cross section times branching ratio limits







Electron ID Neural Network: Powerful Variables



Limit Calculation

- The Poisson probability of n given events occurring (μ is average) is:

$$p(n, \mu) = \frac{e^{-\mu}\mu^n}{n!}$$

Limit Calculation

- The Poisson probability of n given events occurring (μ is average) is:

$$p(n,\mu) = \frac{e^{-\mu}\mu^n}{n!}$$

- Extending to N_b bins and N_C channels and replacing μ with R × s + b (s & b are expected signal and background; R is a multiplicative factor reflecting the sensitivity to signal)

$$\prod_{i=1}^{N_C}\prod_{j=1}^{N_b}\frac{e^{-(R\times s_{ij}+b_{ij})}(R\times s_{ij}+b_{ij})^{n_{ij}}}{n_{ij}!}$$

Limit Calculation

- The Poisson probability of n given events occurring (μ is average) is:

$$p(n, \mu) = \frac{e^{-\mu}\mu^{n}}{n!}$$

- Extending to N_b bins and N_C channels and replacing μ with R × s + b (s & b are expected signal and background; R is a multiplicative factor reflecting the sensitivity to signal)

$$\prod_{i=1}^{N_C}\prod_{j=1}^{N_b}\frac{e^{-(R\times s_{ij}+b_{ij})}(R\times s_{ij}+b_{ij})^{n_{ij}}}{n_{ij}!}$$

- Introduce systematic uncertainties with π(θ), where θ_k is the k-th nuisance parameter

$$\mathcal{L}(R,\vec{s},\vec{b}|\vec{n},\vec{\theta})\times\pi(\vec{\theta}) = \prod_{i=1}^{N_C}\prod_{j=1}^{N_b}\frac{\mu_{ij}^{n_{ij}}e^{-\mu_{ij}}}{n_{ij}!}\times\prod_{k=1}^{n_{np}}e^{-\theta_k^2/2}$$

Limit Calculation

- The Poisson probability of n given events occurring (μ is average) is:

$$p(n,\mu) = \frac{e^{-\mu}\mu^{n}}{n!}$$

- Extending to N_b bins and N_C channels and replacing μ with R × s + b (s & b are expected signal and background; R is a multiplicative factor reflecting the sensitivity to signal)

$$\prod_{i=1}^{N_C}\prod_{j=1}^{N_b} \frac{e^{-(R\times s_{ij}+b_{ij})}(R\times s_{ij}+b_{ij})^{n_{ij}}}{n_{ij}!}$$

- Introduce systematic uncertainties with π(θ), where θ_k is the k-th nuisance parameter

$$\mathcal{L}(R,\vec{s},\vec{b}|\vec{n},\vec{\theta}) \times \pi(\vec{\theta}) = \prod_{i=1}^{N_C}\prod_{j=1}^{N_b} \frac{\mu_{ij}^{n_{ij}} e^{-\mu_{ij}}}{n_{ij}!} \times \prod_{k=1}^{n_{np}} e^{-\theta_k^2/2}$$

- Integrate over the parameter space leaving a function in R, P(R)

$$P(R) = \int \mathcal{L}(R,\vec{s},\vec{b}|\vec{n},\vec{\theta}) \times \pi(\vec{\theta})d\vec{\theta}$$

Limit Calculation

- The Poisson probability of n given events occurring (μ is average) is:

$$p(n,\mu) = \frac{e^{-\mu}\mu^{n}}{n!}$$

- Extending to N_b bins and N_C channels and replacing μ with R × s + b (s & b are expected signal and background; R is a multiplicative factor reflecting the sensitivity to signal)

$$\prod_{i=1}^{N_C}\prod_{j=1}^{N_b}\frac{e^{-(R\times s_{ij}+b_{ij})}(R\times s_{ij}+b_{ij})^{n_{ij}}}{n_{ij}!}$$

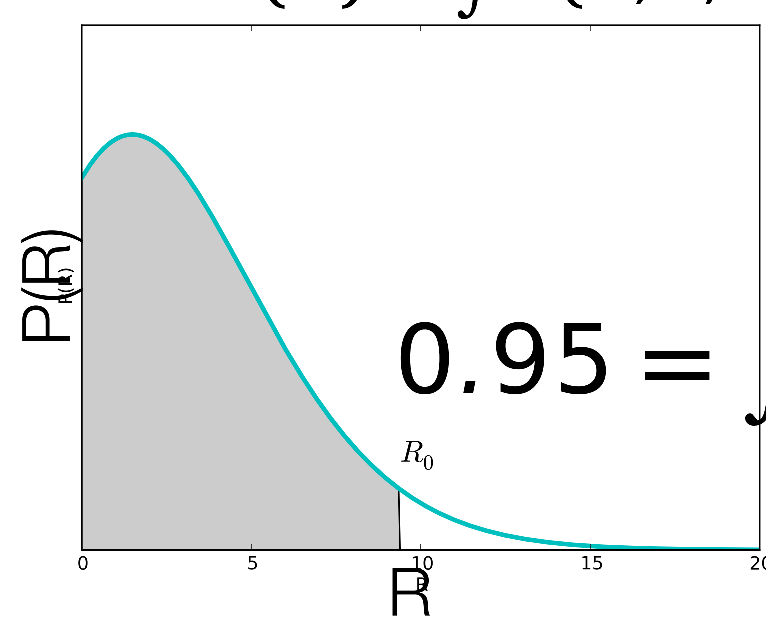
- Introduce systematic uncertainties with π(θ), where θ_k is the k-th nuisance parameter

$$\mathcal{L}(R,\vec{s},\vec{b}|\vec{n},\vec{\theta}) \times \pi(\vec{\theta}) = \prod_{i=1}^{N_C}\prod_{j=1}^{N_b}\frac{\mu_{ij}^{n_{ij}}e^{-\mu_{ij}}}{n_{ij}!} \times \prod_{k=1}^{n_{np}} e^{-\theta_k^2/2}$$

- Integrate over the parameter space leaving a function in R, P(R)

$$P(R) = \int \mathcal{L}(R,\vec{s},\vec{b}|\vec{n},\vec{\theta}) \times \pi(\vec{\theta})d\vec{\theta}$$

- Integrate over P(R) to find 95% coverage (95% confidence level)



$$0.95 = \int_0^{R_0} dR P(R)$$

Limit Calculation

- The Poisson probability of n given events occurring (μ is average) is:

$$p(n,\mu) = \frac{e^{-\mu}\mu^n}{n!}$$

- Extending to N_b bins and N_C channels and replacing μ with R × s + b (s & b are expected signal and background; R is a multiplicative factor reflecting the sensitivity to signal)

$$\prod_{i=1}^{N_C}\prod_{j=1}^{N_b} \frac{e^{-(R\times s_{ij}+b_{ij})}(R\times s_{ij}+b_{ij})^{n_{ij}}}{n_{ij}!}$$

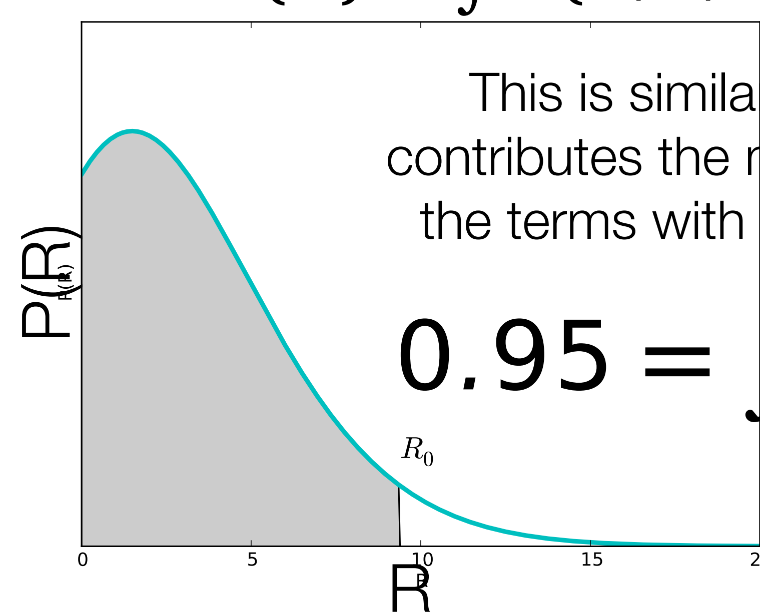
- Introduce systematic uncertainties with π(θ), where θ_k is the k-th nuisance parameter

$$\mathcal{L}(R,\vec{s},\vec{b}|\vec{n},\vec{\theta}) \times \pi(\vec{\theta}) = \prod_{i=1}^{N_C}\prod_{j=1}^{N_b} \frac{\mu_{ij}^{n_{ij}} e^{-\mu_{ij}}}{n_{ij}!} \times \prod_{k=1}^{n_{np}} e^{-\theta_k^2/2}$$

- Integrate over the parameter space leaving a function in R, P(R)

$$P(R) = \int \mathcal{L}(R,\vec{s},\vec{b}|\vec{n},\vec{\theta}) \times \pi(\vec{\theta})d\vec{\theta}$$

- Integrate over P(R) to find 95% coverage (95% confidence level)



This is similar to a fit since what contributes the most to the integral are the terms with the highest likelihood

$$0.95 = \int_0^{R_0} dR P(R)$$

Assigned Systematic Parameters

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)
- cross-section uncertainty: 6% (ZZ, WZ, WW), 40% (Z+heavy flavor), 10% (ttbar)

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)
- cross-section uncertainty: 6% (ZZ, WZ, WW), 40% (Z+heavy flavor), 10% (ttbar)
- Misidentified electrons: 50% (assessed by checking the rates in different jet data sets)

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)
- cross-section uncertainty: 6% (ZZ, WZ, WW), 40% (Z+heavy flavor), 10% (ttbar)
- Misidentified electrons: 50% (assessed by checking the rates in different jet data sets)
- b-tag scale factor: 5.2% (single tight tag), 8.7% (double loose tag), 10.4% (double tight tag)

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)
- cross-section uncertainty: 6% (ZZ, WZ, WW), 40% (Z+heavy flavor), 10% (ttbar)
- Misidentified electrons: 50% (assessed by checking the rates in different jet data sets)
- b-tag scale factor: 5.2% (single tight tag), 8.7% (double loose tag), 10.4% (double tight tag)
- EM energy scale: 3% (acceptance effects of period corrections and plug-energy smearing)

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)
- cross-section uncertainty: 6% (ZZ, WZ, WW), 40% (Z+heavy flavor), 10% (ttbar)
- Misidentified electrons: 50% (assessed by checking the rates in different jet data sets)
- b-tag scale factor: 5.2% (single tight tag), 8.7% (double loose tag), 10.4% (double tight tag)
- EM energy scale: 3% (acceptance effects of period corrections and plug-energy smearing)
- lepton ID scale factor: 2%

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)
- cross-section uncertainty: 6% (ZZ, WZ, WW), 40% (Z+heavy flavor), 10% (ttbar)
- Misidentified electrons: 50% (assessed by checking the rates in different jet data sets)
- b-tag scale factor: 5.2% (single tight tag), 8.7% (double loose tag), 10.4% (double tight tag)
- EM energy scale: 3% (acceptance effects of period corrections and plug-energy smearing)
- lepton ID scale factor: 2%
- ISR/FSR: 4% (effect measured in MC)

Assigned Systematic Parameters

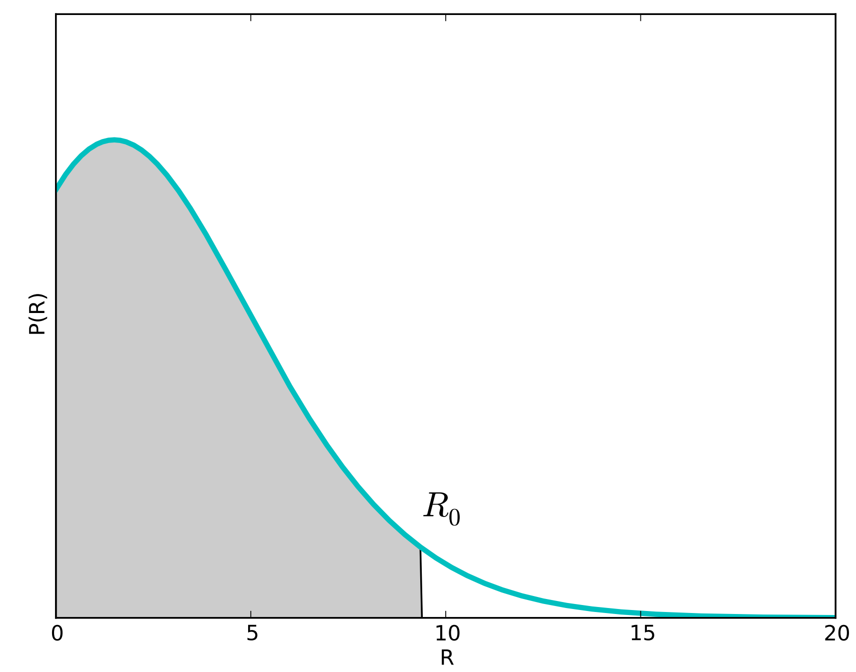
- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)
- cross-section uncertainty: 6% (ZZ, WZ, WW), 40% (Z+heavy flavor), 10% (ttbar)
- Misidentified electrons: 50% (assessed by checking the rates in different jet data sets)
- b-tag scale factor: 5.2% (single tight tag), 8.7% (double loose tag), 10.4% (double tight tag)
- EM energy scale: 3% (acceptance effects of period corrections and plug-energy smearing)
- lepton ID scale factor: 2%
- ISR/FSR: 4% (effect measured in MC)
- Jet-energy scale: shift the jet-energy corrections in MC $\pm\sigma$

Assigned Systematic Parameters

- Luminosity uncertainty: 3.8% (uncertainty in inelastic cross section), 4.4% due in acceptance & efficiency of luminosity monitor)
- Trigger model: 1% (effect measured using different sub-sets of data to train and test the network)
- cross-section uncertainty: 6% (ZZ, WZ, WW), 40% (Z+heavy flavor), 10% (ttbar)
- Misidentified electrons: 50% (assessed by checking the rates in different jet data sets)
- b-tag scale factor: 5.2% (single tight tag), 8.7% (double loose tag), 10.4% (double tight tag)
- EM energy scale: 3% (acceptance effects of period corrections and plug-energy smearing)
- lepton ID scale factor: 2%
- ISR/FSR: 4% (effect measured in MC)
- Jet-energy scale: shift the jet-energy corrections in MC $\pm\sigma$
- Mistagged jets: run on data with parameters $\pm\sigma$

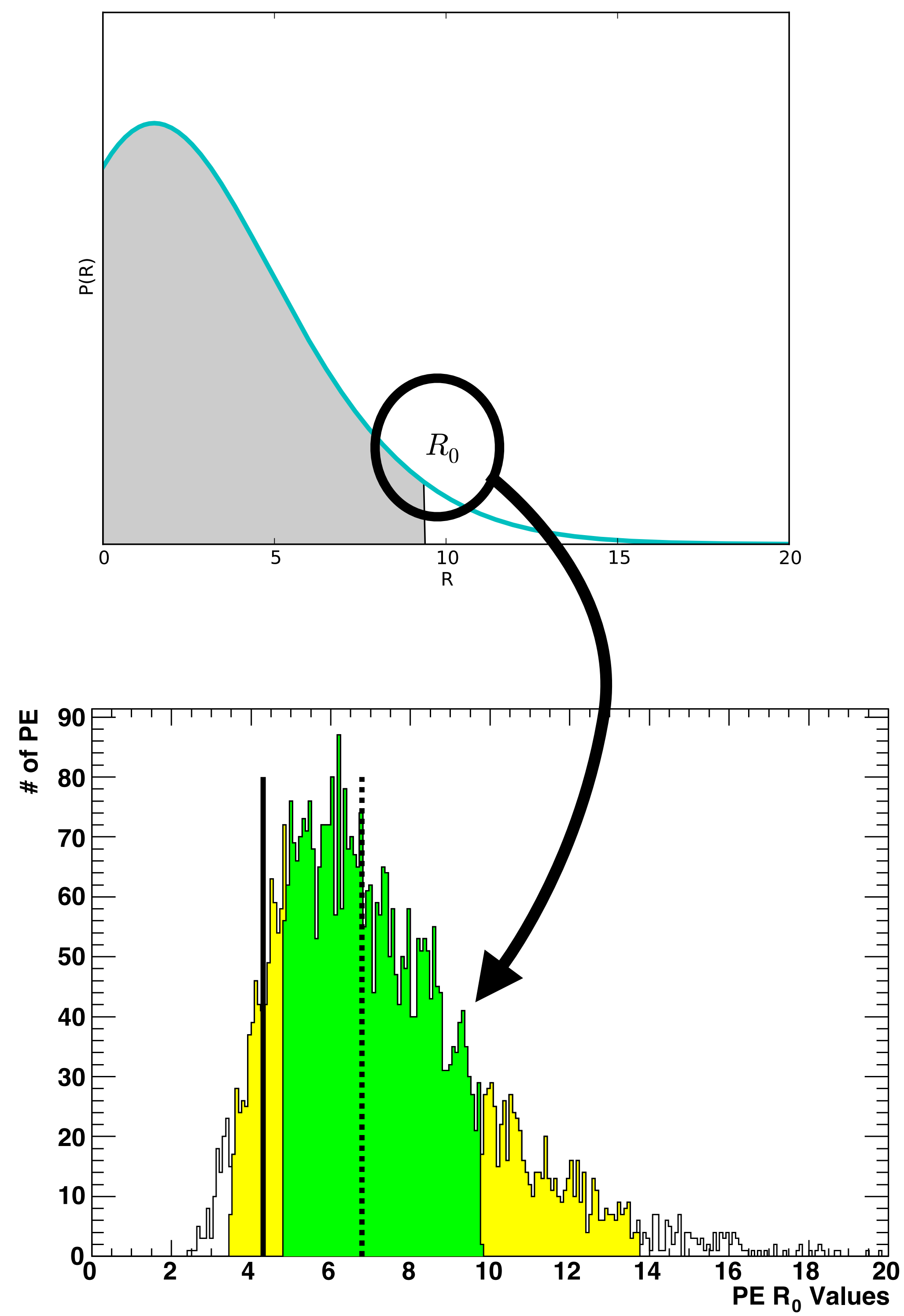
A Word on How We Display the Results

- PE is drawn (from the MC), and integral set up
- The P(R) integral is integrated to the 95% value giving R_0
- (For the expected value) R_0 is entered into a distribution of R_0
- After PEs are done, 1 & 2 σ bands are found
- This is done at each mass point creating this kind of graph
- Observed is treated as separate PE



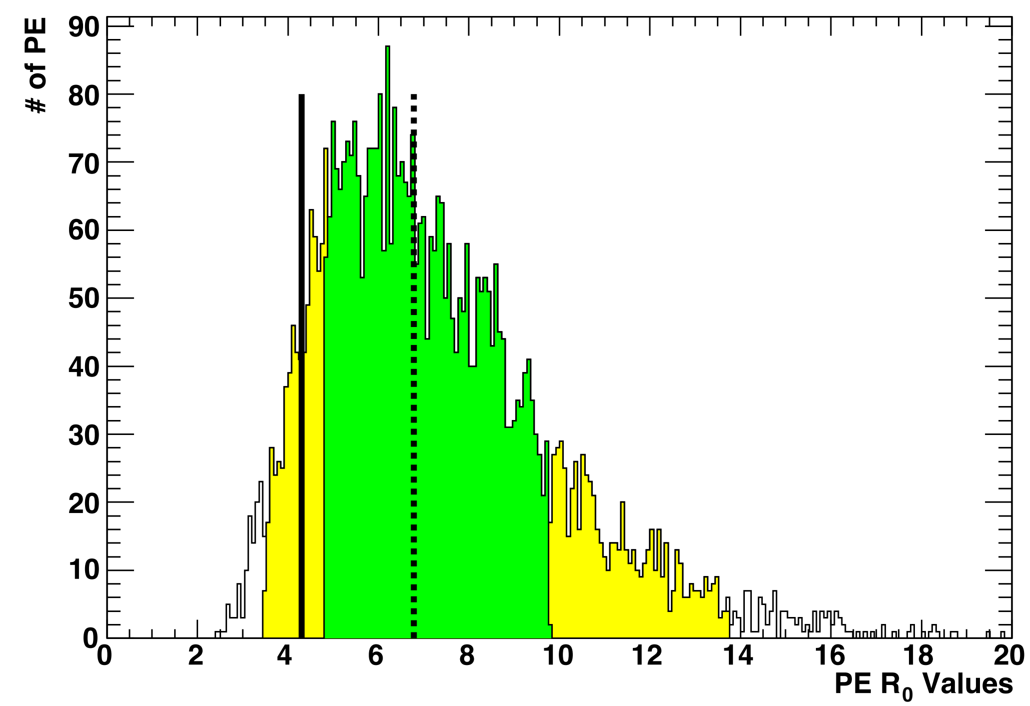
A Word on How We Display the Results

- PE is drawn (from the MC), and integral set up
- The P(R) integral is integrated to the 95% value giving R_0
- (For the expected value) R_0 is entered into a distribution of R_0
- After PEs are done, 1 & 2 σ bands are found
- This is done at each mass point creating this kind of graph
- Observed is treated as separate PE



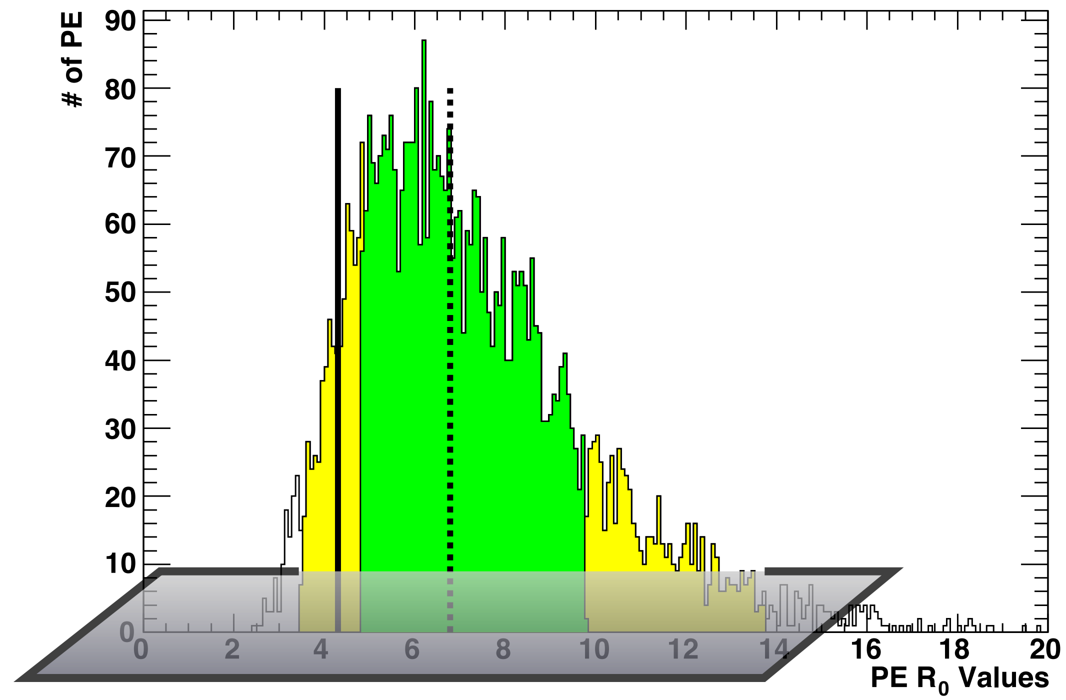
A Word on How We Display the Results

- PE is drawn (from the MC), and integral set up
- The P(R) integral is integrated to the 95% value giving R_0
- (For the expected value) R_0 is entered into a distribution of R_0
- After PEs are done, 1 & 2 σ bands are found
- This is done at each mass point creating this kind of graph
- Observed is treated as separate PE



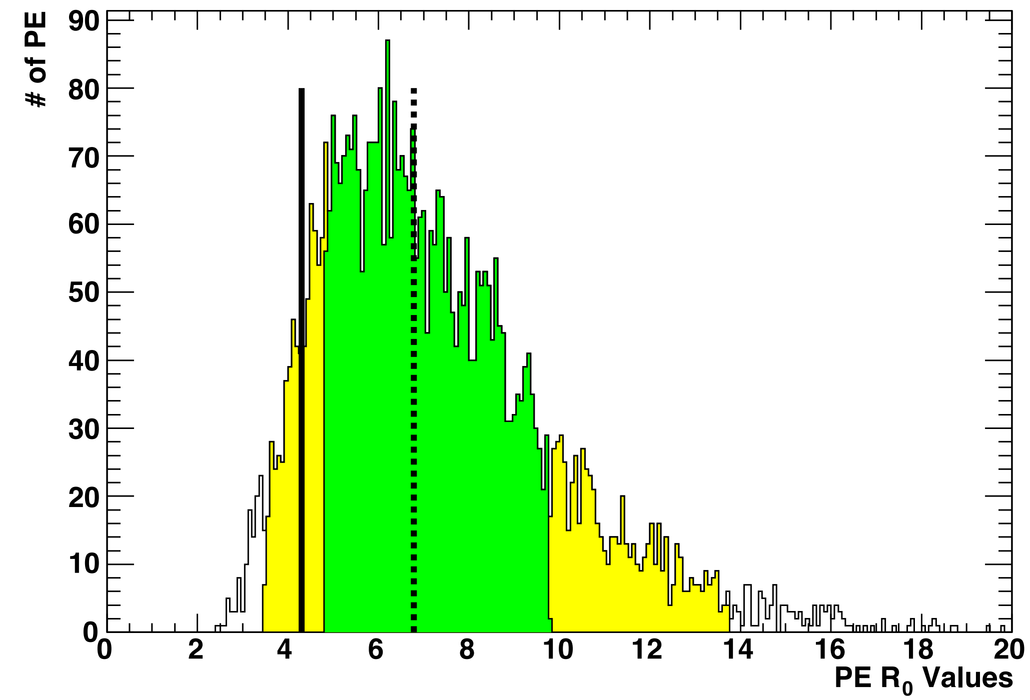
A Word on How We Display the Results

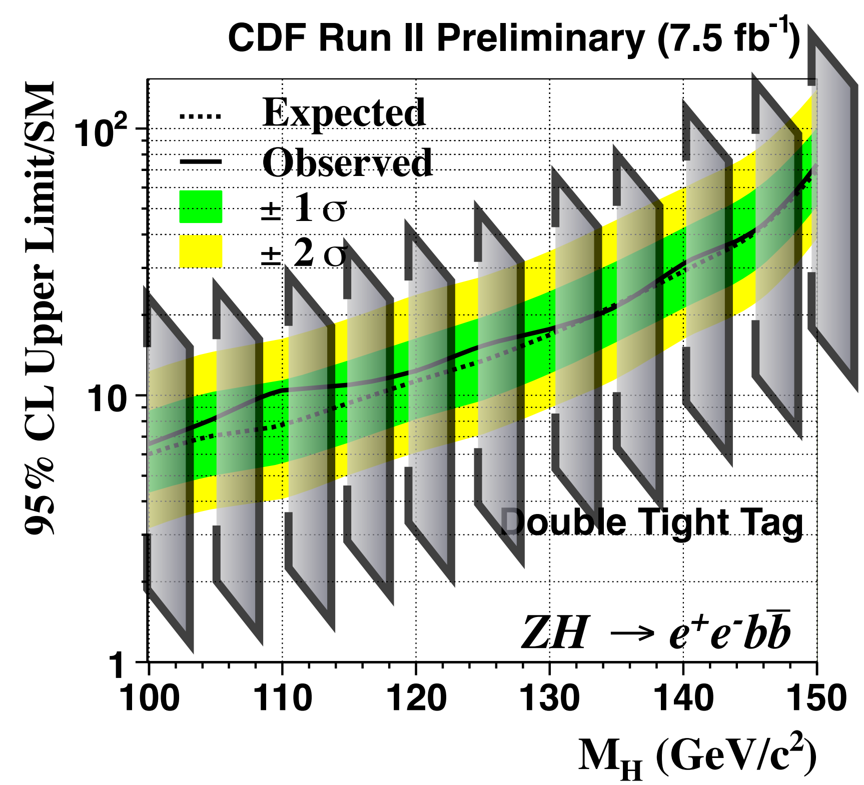
- PE is drawn (from the MC), and integral set up
- The P(R) integral is integrated to the 95% value giving R_0
- (For the expected value) R_0 is entered into a distribution of R_0
- After PEs are done, 1 & 2 σ bands are found
- This is done at each mass point creating this kind of graph
- Observed is treated as separate PE



A Word on How We Display the Results

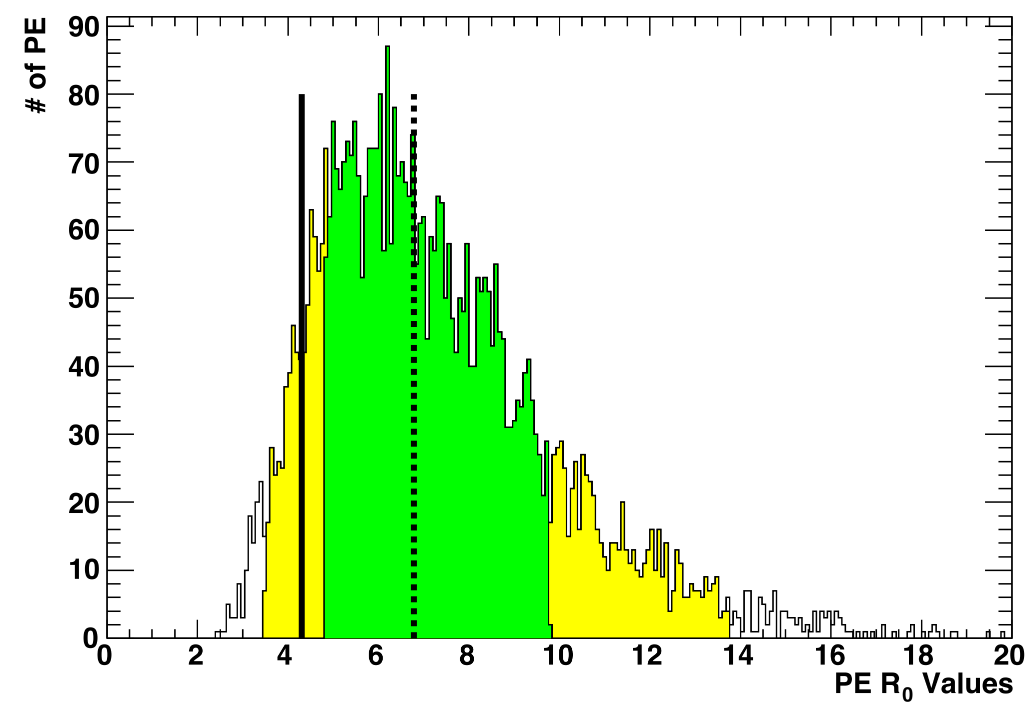
- PE is drawn (from the MC), and integral set up
- The P(R) integral is integrated to the 95% value giving R_0
- (For the expected value) R_0 is entered into a distribution of R_0
- After PEs are done, 1 & 2 σ bands are found
- This is done at each mass point creating this kind of graph
- Observed is treated as separate PE

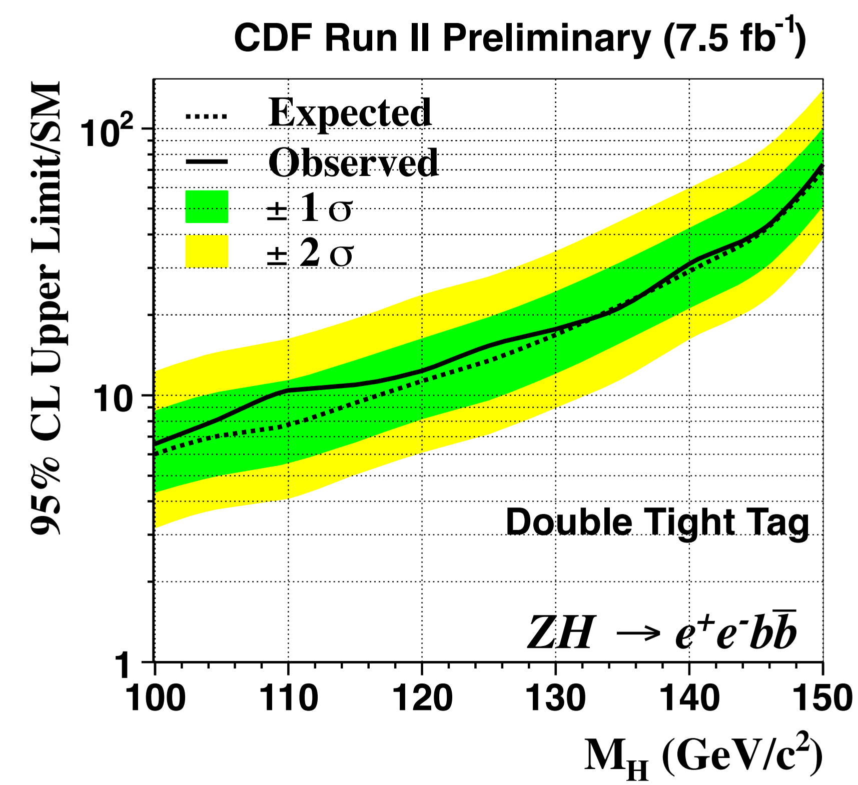




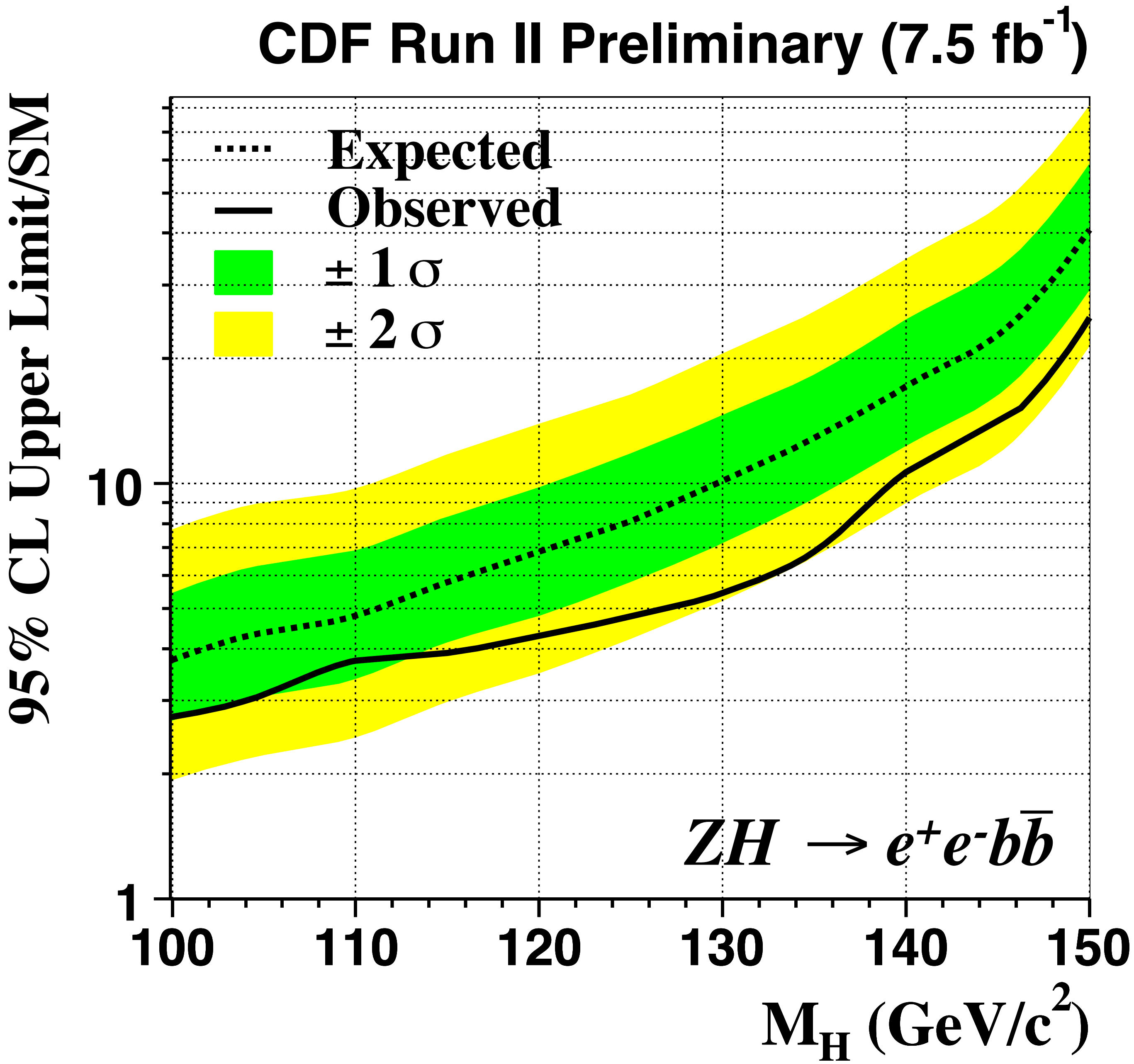
A Word on How We Display the Results

- PE is drawn (from the MC), and integral set up
- The P(R) integral is integrated to the 95% value giving R_0
- (For the expected value) R_0 is entered into a distribution of R_0
- After PEs are done, 1 & 2 σ bands are found
- This is done at each mass point creating this kind of graph
- Observed is treated as separate PE





Result: ZH to eebb



$ZH \to e^+e^-b\bar{b}$ Limits. CDF Run II Preliminary (7.5 fb^{-1})

ZH Mass	Observed Limit	Expected Limit -2σ	-1σ	Median	+1σ	+2σ
100	2.74	1.94	2.67	3.75	5.41	7.71
105	2.97	2.17	2.99	4.26	6.17	8.73
110	3.74	2.46	3.36	4.80	6.86	9.68
115	3.91	3.00	4.13	5.79	8.28	11.69
120	4.29	3.51	4.77	6.85	9.75	13.83
125	4.79	4.25	5.76	8.12	11.75	16.30
130	5.44	5.24	7.14	10.14	14.52	20.45
135	6.84	6.68	9.15	12.84	18.18	25.76
140	10.66	9.02	12.25	17.10	24.68	34.53
145	15.16	13.22	18.10	25.42	36.49	51.31
150	25.05	21.59	28.95	40.78	58.39	80.87

Extras!

EM:

Central: $\frac{\sigma(E_T)}{E_T} = \frac{13.5\%}{\sqrt{E_T}} \oplus 2\%$

Forward: $\frac{\sigma(E)}{E} = \frac{16\%}{\sqrt{E}} \oplus 1\%$

Hadronic:

Central: $\frac{\sigma(E_T)}{E_T} = \frac{75\%}{\sqrt{E_T}} \oplus 3\%$

Forward: $\frac{\sigma(E)}{E} = \frac{80\%}{\sqrt{E}} \oplus 5\%$

PreTag Zs	Fired	Fired Excl.
Single e	74.6%	5.96%
2 Cal Deposits	84.8%	6.01%
New Trigger	69.0%	**5.09%**

Extras!

	High	Low
Central	0.75	0.3
Forward Phoenix	0.5	0
Forward Non-Phx	0.6	0.3

Score Range [-1,1]

EM:

Central: $\frac{\sigma(E_T)}{E_T} = \frac{13.5\%}{\sqrt{E_T}} \oplus 2\%$

Forward: $\frac{\sigma(E)}{E} = \frac{16\%}{\sqrt{E}} \oplus 1\%$

Hadronic:

Central: $\frac{\sigma(E_T)}{E_T} = \frac{75\%}{\sqrt{E_T}} \oplus 3\%$

Forward: $\frac{\sigma(E)}{E} = \frac{80\%}{\sqrt{E}} \oplus 5\%$

PreTag Zs	Fired	Fired Excl.
Single e	74.6%	5.96%
2 Cal Deposits	84.8%	6.01%
New Trigger	69.0%	**5.09%**

Making Z's

Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value

Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value

	High	Low
Central	0.75	0.3
Forward Phoenix	0.5	0
Forward Non-Phx	0.6	0.3

Score Range [-1,1]

Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value

Score selection:
While maximizing a significance value was pursued, it led to extreme cut-values. Values selected by taking the best Z mass distribution in data (also check MC)

	High	Low
Central	0.75	0.3
Forward Phoenix	0.5	0
Forward Non-Phx	0.6	0.3

Score Range [-1,1]

Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value
- Reject Non-Phx + Non-Phx objects

Score selection:
While maximizing a significance value was pursued, it led to extreme cut-values. Values selected by taking the best Z mass distribution in data (also check MC)

	High	Low
Central	0.75	0.3
Forward Phoenix	0.5	0
Forward Non-Phx	0.6	0.3

Score Range [-1,1]

Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value
- Reject Non-Phx + Non-Phx objects
- Additionally allow a high-score central electron to be paired with a *crack-track* electron
  - Crack-track electrons are cut-based (track points to an uninstrumented part of the calorimeter)

Score selection:
While maximizing a significance value was pursued, it led to extreme cut-values. Values selected by taking the best Z mass distribution in data (also check MC)

	High	Low
Central	0.75	0.3
Forward Phoenix	0.5	0
Forward Non-Phx	0.6	0.3

Score Range [-1,1]

Making Z's

- A Z object is formed by
  - One electron with a score greater than a ***High*** value
  - Plus another electron with a score greater than a ***Low*** score value
- Reject Non-Phx + Non-Phx objects
- Additionally allow a high-score central electron to be paired with a *crack-track* electron
  - Crack-track electrons are cut-based (track points to an uninstrumented part of the calorimeter)
- We have a mass cut of 76-106 GeV/c^2 and an opposite charge req. for central+central events

Score selection:
While maximizing a significance value was pursued, it led to extreme cut-values. Values selected by taking the best Z mass distribution in data (also check MC)

	High	Low
Central	0.75	0.3
Forward Phoenix	0.5	0
Forward Non-Phx	0.6	0.3

Score Range [-1,1]